FOUR PAPERS ON STRUCTURAL HOUSEHOLD WELFARE DYNAMICS

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Despite recent progress, abject poverty remains pervasive in many countries around the world. Achieving further sustained reductions in poverty will require more effective poverty eradication policies. The effectiveness of these policies, in turn, depends on how well we understand the structural dynamics of households moving in and out of poverty.

The four papers in this dissertation explore several issues in the modeling and measurement of structural household welfare dynamics that to date have received little attention in the academic literature but that are directly relevant for the design of poverty reduction policies.

The first paper examines quantitative methods for modeling household welfare dynamics and identifying long-run welfare equilibria and poverty traps. It proposes a new semiparametric panel data estimator that has several advantages over methods used in the extant literature. The empirical application to data from three Indian villages shows deep structural immobility. Structural poverty traps loom large, as rural Indian households who start out asset-poor are likely to remain poor.

The second paper proposes and applies a statistical test to examine whether high estimates of economic mobility and transitory poverty in the existing literature are

partially driven by stochastic one-off income flows. It finds that these estimates are inversely correlated to the length of the interval between panel observations suggesting that estimates based on short panel spells represent (high) upper bounds of underlying structural economic mobility and (low) lower bounds of chronic poverty.

The third paper introduces several new classes of intertemporal poverty measures that can incorporate the variability of household welfare and the distribution of poverty across households over time. Accounting for these intertemporal factors in rural Pakistan leads to greater estimates of poverty than using existing, static poverty indicators.

The fourth paper uses a regression-based technique to explore the household characteristics that determine income inequality in rural Pakistan. The level of inequality is determined primarily by land ownership and location. These structural variables are difficult to change by policy, in contrast to the factors that reduced inequality over time, such as access to secondary education and lower dependency ratios.

BIOGRAPHICAL SKETCH

Felix Naschold was born in 1972 in Porto Alegre, Brazil. After attending schools in Germany and Sri Lanka he graduated with an International Baccalaureate in 1990. He earned a BSc(Econ) in Economics from the University College London in 1994, and an MSc in Development Economics from the School of Oriental and African Studies at the University of London in 1995. The following two years he worked as an economic advisor to the Ministry of Finance and Economic Development in Fiji, where he also met his wife Christine Porter. After returning to London in 1998 Felix spent four years as a researcher and international consultant at the Overseas Development Institute working on poverty monitoring and public expenditure reform policies in developing countries. In 2002 he returned to academia and began his PhD in Development Economics in the Department of Applied Economics and Management at Cornell University in Ithaca, New York. The ensuing five years led to these dissertation papers and saw the arrival of his two daughters, Isabel and Alexa.

Für meine Lieblings.

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Chapter 1:
Introduction

Context and Research Questions

In the Millennium Development Goals the world community committed itself to substantial improvements in human well-being with the central goal of halving poverty rates by 2015. While there has been substantial progress towards this goal in some regions of the world, abject poverty remains all too common. In 2004 around 1 billion of the world's population continues to live on less than one dollar a day, and more than 2.5 billion subsist on less than two dollars (World Bank 2007). The magnitude of this human misery remains enormous and presents formidable challenges, particularly in rural areas of many developing countries.

Quicker and more sustained progress towards reducing poverty requires more effective public policies. Enhancing the effectiveness of these poverty reduction policies, in turn, depends heavily on improving our understanding of household welfare dynamics. Only if we know more about the processes and dynamics of how households escape and fall into poverty over time can we better target assistance. Given the importance and the magnitude of the challenge to reduce poverty, it is surprising and unfortunate how little we know to date about these dynamics.

This dissertation is motivated by this twin challenge: tackling interesting academic research questions on household welfare dynamics which, at the same time, have direct practical relevance and the potential to inform the design of more effective poverty reduction policies. These four papers on household welfare dynamics explore different aspects of this challenge. They, respectively, address the following key research questions:

1. What quantitative methods are most appropriate to model household welfare dynamics and to uncover potential poverty traps?
2. To what extent are estimates of welfare dynamics and economic mobility affected by the length of time over which surveys observe households?
3. How can households' experiences of poverty over time be measured to take account of welfare variability for individual households and of the intertemporal distribution of poverty across households?
4. What household level factors determine the level of economic inequality, and what factors explain changes to inequality over time?

The new methods developed in the four papers are tested in empirical applications to two panel datasets covering rural households in South Asia where poverty is structurally deeply entrenched. The ICRISAT Village Level Studies (VLS) panel follows households in three villages in semi-arid India from 1975/76 to 2003/04, making it the longest running panel dataset in any developing country and, thus, ideally suited to exploring household welfare dynamics. The IFPRI Pakistan Rural Household Survey (PRHS) describes rural households in four districts over the period 1986/87 to 1990/91.

An Introduction to the Four Papers

Modeling Household Asset Dynamics

The first paper *Modeling Household Asset Dynamics: New Methods with an Application to Rural India* quantitatively explores the dynamics of household welfare changes. It lays out the deficiencies of the methodological toolkit used in the existing empirical literature on household welfare dynamics (Jalan and Ravallion 2004; Lokshin and Ravallion 2004; Barrett *et al.* 2006). It then introduces a more robust semiparametric panel data estimation technique that is more suitable for modeling household asset dynamics and precisely locating dynamic asset equilibria. Also, its empirical application contributes to the small emerging empirical literature on non-linear household welfare dynamics by providing the first study for rural India, a country which is home to almost 40% of the world's population living on less than one dollar per day (World Bank 2007).

Identifying the shape of household welfare dynamics and the equilibrium level of long term household welfare poses a difficult academic challenge, both in terms of methods and data requirements. Yet, it is also highly relevant for designing effective anti-poverty policies. If there is a single welfare equilibrium to which all households gravitate in the long run, we need to know its level. If it is sufficiently high to escape poverty, then policy can focus on helping households move along the dynamic welfare path more quickly. In contrast, an equilibrium below the poverty line would constitute a poverty trap and require structural changes that provide new economic opportunities for households.

Alternatively, household welfare dynamics may exhibit multiple dynamic welfare equilibria with threshold points above which households will move towards a higher level of welfare, and below which households converge towards another, low-level equilibrium. If this lower level of welfare lies below the poverty line then the threshold point would constitute the entrance to a dynamic poverty trap. Households can be chronically poor simply by starting out poor. Clearly, the policy response in such a world would differ markedly from the single equilibrium case, requiring policies to lift households above the threshold point and social protection measures to ensure that households don't fall below the thresholds in the aftermath of adverse shocks.

This paper uses a definition of household welfare based on assets stocks rather than income or expenditure flows. This is particularly appropriate in a dynamic context and helps to identify structural poverty. Ultimately, it is asset holdings that, conditional on production technologies and market prices, determine a household's level of material well-being. Thus, relative to income or expenditure flows, observing asset stocks generates more information about which households are likely to be poor in the future, which can improve the targeting of public policies (Carter and Barrett 2006).

The empirical application to data from three Indian villages portrays a society characterized by pervasive structural immobility and economic stagnation. Despite a very slow upward trend over the last 30 years, a large proportion of village households simply remain at their initial welfare level. This suggests a strong type of poverty trap: absent any structural changes, (in expectation) the currently poor remain poor. The most precise estimates from the new semiparametric estimation technique suggests that the median household in the villages already attained the equilibrium level of welfare in 2001, suggesting that the concurrent consumption poverty rate of 22% is likely to persist in the absence of structural change that increases villagers' productivity.

Finally, disaggregating the results by subgroup shows a predictable pattern. Higher castes, larger landholders and more educated households enjoy monotonically greater welfare equilibria than their lower caste, smaller landholder and less educated peers.

Economic Mobility the Length of Observation

The second paper, entitled *Do Short-Term Observed Income Changes Overstate Structural Economic Mobility?,* is motivated by the recent empirical literature on household income dynamics in developing countries which has tended to find a high degree of economic mobility and, consequently, concluded that a large proportion of poverty is transitory (Baulch and Hoddinott 2000; McCulloch and Baulch 2000). This paper investigates what we can infer from these results in terms of the underlying structural economic mobility that is the focus of long-term poverty reduction efforts.

We can think of total economic mobility as comprised of structural and stochastic economic mobility. Structural economic mobility results from changes in non-stochastic income resulting both from changes in household assets and changes in expected returns to these assets. Stochastic mobility in contrast is due to changes in stochastic transitory income as well as changes in measurement error.

This definition frames the central argument in this paper: If we don't control for stochastic factors and, thus, implicitly assume that total economic mobility measures structural mobility, then the length of the interval between panel rounds influences the estimate of economic mobility. If the random components of the income changes observed in the panel survey, i.e., one-off stochastic transitory income and measurement error, are independently distributed then we should expect shorter intervals to lead to larger estimates of economic mobility and transitory poverty. A statistical test to verify this hypothesis is proposed and applied to the PRHS data from rural Pakistan.

Previous work using the same data (Baulch and McCulloch 1998) concluded that only 3 percent of households are poor in all five years of the panel. This suggests a very high degree of transitory poverty and economic mobility (around the poverty line) and makes the PRHS data well-suited to testing whether the observation spell length influences the estimates.

By controlling for measurement error the paper partially filters out this second random component of observed household income. This allows the test to concentrate on the effect of stochastic transitory income. The results based on the PRHS data confirm that economic mobility and the transitory share of poverty are, indeed, inversely correlated to the interval between panel observations.

This indicates that estimates of total economic mobility capture structural economic mobility better when observed spells are longer. An obvious corollary is that total economic mobility estimates based on short panel data spells need to be interpreted with caution, suggesting that the high estimates of economic mobility and transitory poverty found in the existing literature represent (high) upper bounds of underlying structural economic mobility and (low) lower bounds of chronic poverty.

Measuring Poverty over Time

The third paper in this dissertation is entitled *Measuring Poverty over Time: Accounting for Income Variability and the Intertemporal Distribution of Poverty*. Poverty is not a static, one-off experience that can be characterized by a single poverty measure at one point in time. Periods spent in poverty can have a range of negative dynamic repercussions for individual and households, e.g., caused by stigma costs, dynamic poverty traps, and preferences for stable welfare levels.

The dynamic aspects of poverty have long been part of qualitative research but quantitative poverty analysis tends to focus on static, single-period, snapshot views. With a growing availability of panel data it is now possible to incorporate poverty dynamics in quantitative analysis, too. However, to date there have been few attempts in the development economics literature to expand static poverty measures to an intertemporal setting.

This paper examines two intertemporal extensions to the standard Foster-Greer-Thorbecke (Foster *et al.* 1984) (FGT) poverty indices and, for each, proposes a variety of suitable classes of measures. The first extension incorporates welfare variability into a measure of intertemporal household poverty. Two classes of measures are proposed based on the assumption that welfare variability reduces intertemporal household well-being. One, based on constant equivalent income, calculates the unique average household income over time that would result in the same amount of household poverty as the household's actual income history. As a result, periods spent in poverty are never 'forgotten'. This measure is appropriate if the goal is to minimize the number of ever-poor households, for example, if households cannot fully recover from periods spent in poverty due to physical irreversibility or stigma. It is also relevant when escaping poverty is difficult due to thresholds effects in household welfare dynamics.

The second, based on stability equivalent, penalizes household welfare variability at all parts of the distribution. It is particularly appropriate to account for welfare variability when there are no thresholds effects associated with becoming poor.

The second intertemporal extension to static FGT measures accounts for the intertemporal distribution of poverty across households, i.e., the degree to which experiences of poverty are shared across households over time. To capture this, two new classes of measures are proposed and a third is derived based on Borooah's (2002) measure of unemployment. These measures are compared to the one other indicator proposed in the literature to date (Basu and Nolen 2006).

All of these intertemporal measures of poverty increase with greater levels of structural immobility and chronic poverty. The applications to the PRHS panel data show that accounting for income variability and the intertemporal distribution of poverty across households makes a substantial practical difference to how we assess poverty over time.
Compared to standard static poverty measures, all the proposed new methods increase estimates of poverty. The size of the increase depends on the distribution of income in each district. As a consequence, accounting for welfare variability and the distribution of poverty across households can change the poverty rankings between districts.

Applying any of the proposed intertemporal extensions involves making some explicit value judgments, for example in choosing one technique over another or in choosing value of parameters. The commonly applied static poverty measures that are the workhorse of (policy) analysis, however, are not free of these value judgments; they simply make them implicitly.

Determinants of Inequality and its Changes

The fourth paper, on *Microeconomic Determinants of Income Inequality in Rural Pakistan,* explores the causes of the level of income inequality and its changes. It is motivated by two observations. On the one hand, a consensus has emerged that income inequality matters for poverty reduction, directly through its effects on the distribution of gains from economic growth as well as indirectly by raising the rate of future growth. On the other, there is surprisingly little quantitative evidence about the types of determinants of static and dynamic inequality that are relevant for policy planning purposes.

Traditional income inequality decompositions are limited to decomposing outcomes either in terms of income sources (Shorrocks 1982), for instance, identifying the proportion of total inequality due to, say, labor and non-labor household income, or by subgroup (Shorrocks 1984), that is, examining the proportion of total inequality that is due to difference within and between subpopulations. In contrast, this paper decomposes income inequality in terms of the underlying drivers of income itself. By adapting Fields' (2003) regression-based inequality decomposition technique it can explain income inequality by any factor for which data is available in a household survey. Thus, it can examine the impact on income inequality of specific household characteristics, such as education, asset holdings or location; that is, in terms of variables that offer more direct insights for policy purposes. Furthermore, the paper extends the regression-based decomposition technique to panel data. This represents a convenient method to explore the determinants of inequality changes over time, and differentiate whether these changes occurred due to changes in the distribution of underlying factors or due to changes in the returns to these factors.

The results from the PRHS data show that the factors that explain the level of income inequality differ from those that explain changes in income inequality in rural Pakistan. The level of income inequality is driven by land ownership and geographical location with owners of small non-irrigated plots in remote areas being worst off. These two variables change slowly over time, if at all. This is consistent with overall structural asset immobility. The small overall net increase in income inequality results from two opposite forces: Inequality increasing factors, which are similar to those explaining the level of inequality such as physical asset holdings and household location; and inequality reducing factors including greater secondary education and a lower dependency ratio. Clearly, changing the distribution of land and location is either impractical or impossible. Thus, if reducing income inequality in rural Pakistan is considered desirable, whether for its own sake or to increase future levels of economic growth and poverty reduction, then policy efforts should focus on improving access to secondary education and market access for remote households, and avoid any new measures that may further skew the distribution of land.

Summary

Despite recent progress, abject poverty remains pervasive in many countries around the world. Achieving further sustained reductions in poverty will require more effective poverty eradication policies. The effectiveness of these policies, in turn, depends on how well we understand the structural dynamics of households moving in and out of poverty.

The four essays in this dissertation explore several issues in the modeling and measurement of structural household welfare dynamics that to date have received little attention in the academic literature but that are directly relevant for informing the design of poverty reduction policies: modeling households' asset accumulation dynamics and identifying long-run welfare equilibria and poverty traps, examining the robustness of economic mobility and transitory income estimates to changes in the observation period, measuring poverty over time when welfare is variable and poverty is unequally distribution across households, and identifying the drivers of income inequality and its changes over time.

The applications to two panel datasets from south Asia show rural societies that are characterized by a large degree of economic stasis and structural welfare immobility. Structural poverty traps – albeit not multiple equilibrium poverty traps – appear a serious concern, as rural Indian households accumulate assets slowly, if at all. Thus, households who start out asset-poor are likely to remain poor absent any structural changes in the rural economy.

Similarly, in rural Pakistan the level of income inequality is explained primarily by structural factors, such as land ownership and location. These are some of the same

factors that determine future productivity and income. However, since these are also factors which change little over time, they suggest a low level of structural economic mobility, mirroring the situation in the Indian villages.

The findings in this dissertation also highlight that due to the short intervals between panel observations, common estimates of total economic mobility overstate the degree of underlying structural mobility. The estimates in the existing literature should, therefore, be interpreted as high upper bounds for structural economic mobility and as low lower bounds for chronic poverty.

Finally, this dissertation proposes several new classes of intertemporal poverty measures. These expand existing, static Foster-Greer-Thorbecke poverty measures to explicitly account for two intertemporal dimensions of poverty: variability in household welfare and the distribution of poverty across households over time. Applying these new classes of measures to rural Pakistan demonstrates that controlling for these intertemporal dimensions leads to greater estimates of poverty than those suggested by existing, static poverty indicators.

The overarching motivation for this dissertation has been to produce new techniques and empirical insights that have a practical policy application. It is my hope that these papers will become a useful addition to the toolkit of household welfare analysis and perhaps ultimately help improve the design of long-term policies aimed at reducing structural poverty.

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Chapter 2:
Modeling Household Asset Dynamics:
New Methods with an Application to Rural India

1 Introduction

Alleviating poverty is one of the key challenges for the new millennium. Meeting this challenge requires effective poverty reduction policies. Designing these policies, in turn, requires an understanding of the underlying welfare dynamics that determine how individuals and households escape or fall into poverty over time. Policy makers need information on two key issues: First, on the location of the dynamic household welfare equilibria towards which people converge over time, as this will indicate whether households are trapped in poverty given current economic opportunities and returns. Second, on the shape of household welfare dynamics, as this will reveal the dynamic nature of possible poverty traps.

If there is but one dynamic equilibrium, the key questions then would be what this equilibrium level of welfare is relative to the poverty line and how quickly households move towards it. If it is sufficiently high for households to escape poverty, then policy can focus on speeding up the convergence process. In contrast, a dynamic equilibrium below the poverty line would suggest that eventually all households are expected to be trapped in poverty. Overcoming such a structural poverty trap would require structural changes that provide new economic opportunities for households that raise their equilibrium level of welfare.

If, instead, there are multiple dynamic welfare equilibria, a household's long-term welfare depends on its initial condition. If it starts above a dynamic threshold, in expectation it will move towards a higher level of welfare. A starting position below the threshold would put it onto a path towards another, low-level equilibrium. If this lower level of welfare lies below the poverty line then the threshold point would constitute the entrance to a second type of poverty trap. Clearly, the policy response in such a world would differ markedly from the single equilibrium case. It would require social policies to lift households above the threshold point and social protection measures to ensure that households don't fall below the thresholds in the aftermath of adverse shocks. A short term public investment in these social policies could harness the dynamic welfare process and yield large long term welfare benefits. Again, for the policies to be efficient, we would need to identify the precise location of the threshold point.

Improving methods for identifying the shape of welfare dynamics and precisely locating dynamic welfare equilibria is, therefore, not just an interesting academic challenge that has not been explored in much detail in the empirical development literature. It is also of great practical importance.

This paper contributes to our knowledge on household welfare dynamics in three ways. First, it compares existing empirical techniques for modeling household welfare dynamics by applying them to the same dataset. This helps to determine whether, and how, the modeling of household welfare dynamics is affected by choosing parametric versus nonparametric techniques and, by extension, provides some indication about whether the different shapes of the welfare dynamics and the different number of dynamic equilibria identified in the existing literature are likely due to differences in estimation methods or to real differences in the datasets used. Second, it introduces and expands a semiparametric panel data estimation technique from the statistics literature that has several features that make it more suitable for modeling household asset dynamics and precisely locating asset equilibria than the techniques used in existing studies. Third, it contributes to the small emerging empirical literature on non-linear household welfare dynamics by providing the first case study for India. It uses the newly expanded ICRISAT Village Level Studies panel dataset which now spans 27 years with 13 observations per household. The long time span and the frequent observations make it ideally suited to exploring the shape of long-term household welfare dynamics and their associated equilibria.

The empirical results suggest that these village economies are characterized by economic stasis. Household asset holdings are effectively at a static equilibrium. Over time asset levels follow a random walk where a household can expect to remain at its current level of asset welfare. Given this lack of dynamism it is not surprising that using more flexible econometric techniques to model asset holdings does not alter the results.

The remainder of the paper is organized as follows. The next section summarizes three competing theories of household welfare dynamics and provides a stylized theoretical framework that guides the analysis in this paper. Section 3 reviews the small empirical literature on modeling non-linear household welfare dynamics. Sections 4 and 5 introduce the data and construct the asset index that is needed for the subsequent asset dynamics analysis. Sections 6 reviews econometric methods used in the existing microeconomic welfare dynamics literature and introduces a new semiparametric panel data technique. Results for all these different estimation techniques are presented in section 7. Section 8 concludes.

2 Theories of Welfare Dynamics

Three main hypotheses from the macroeconomic literature on growth dynamics can inform the analysis of micro-level dynamic poverty traps: unconditional convergence, conditional convergence and multiple dynamic equilibria (Carter and Barrett 2006).

The concept of unconditional convergence originates from the Solow growth model. In the context of household level dynamics it suggests that all households eventually gravitate to the same long term equilibrium, based on the assumption that asset dynamics for all households follow a common, concave, monotone Markov process. The dynamics underlying the conditional convergence hypothesis are the same. It expands the unconditional convergence concept simply by allowing exogenous subgroups to have a different dynamic path and equilibrium.

A priori, there is no clear reason why asset dynamics should follow an autoregressive process of this form. On the contrary, at least four theoretical models suggest that different types of nonconvexities can result in multiple dynamic equilibria and in poverty traps if the lower stable equilibrium is below the poverty line.

First, the efficiency wage hypothesis (Mirrlees 1975; Stiglitz 1976; Dasgupta and Ray 1986; Dasgupta 1997) links worker productivity and earnings. Only if a worker can afford to consume more than a minimum level will he be productive and, hence, employed. Others who are unable to afford the minimum level of consumption remain poor. Second, limited access to credit or formal and informal insurance can limit a household's ability to invest in human capital (Loury 1981; Galor and Zeira 1993) or in an income-generating opportunity (Banerjee and Newman 1993). As a result any household dynasty starting below a certain level of wealth, or suffering a shock large enough to let it fall below this threshold, will be trapped in poverty. Third, if participating in society and finding employment require minimum levels of expenditure (Bradshaw 1993; Parker 1998), then poor households can be permanently 'socially excluded'. Fourth, child labor models (Basu 1999; Emerson and Souza 2003) suggest that poor households that have to send their children to work instead of school are trapped in intergenerational poverty since as adults these children do not possess the qualifications to access opportunities to escape poverty.

All these theoretical models have similar policy implications: if there are multiple dynamic equilibria with one stable equilibrium below the poverty line then the misfortune to start with low asset holdings or the realization of downside risk are structural causes of chronic poverty. Conversely, poverty traps and long term poverty could be eliminated if every household can be lifted above the unstable equilibrium threshold and if safety nets ensured that they remained there. Hence, one-off social expenditures would not only benefit households in the current period, but also result in higher welfare in all future periods. Current social expenditure would yield high long run returns.

The above theoretical models can be stylized by recursion diagrams in household asset space as shown in Figure 1. The recursion functions denote expected household asset accumulation paths. The horizontal and the vertical axes display household asset holdings in the previous and in the current time period, respectively $A_{t+1}$and A_t. Any point on the 45-degree line represents a dynamic asset equilibrium. Function $f_1(A_t)$ illustrates the case of multiple dynamic equilibria where the dynamic asset accumulation path crosses the 45-degree line several times. A precondition for the existence of multiple equilibria are non-convexities over at least a part of the asset domain. If the poverty line lies above A* then the unstable equilibrium point A' indicates a dynamic asset poverty threshold. Above this threshold point and absent any negative asset shocks households can be expected to accumulate further until they reach the high level long-run equilibrium point A**. Below A' households are on a trajectory which, in expectation, makes them poorer over time, moving towards the low-level poverty equilibrium at A*.

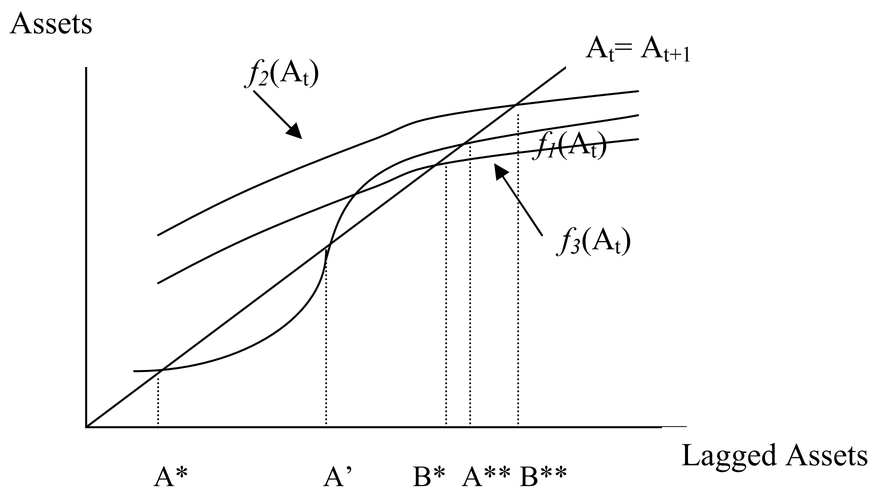

Figure 1 Stylized Asset Recursion Diagram for Different Shapes of the Asset Accumulation Path

Since these threshold points represent unstable equilibria a priori we might expect them to lie in a low density region of the distribution (Barrett and McPeak 2005), because in equilibrium households would be at either of the two stable equilibrium points. If this is the case we need estimation techniques that can identify these unstable equilibria using relatively few data points around A'. Fully parametric techniques would be at a clear disadvantage as the estimated polynomial function would be driven by the mass of observations around A* and A**, likely leading to imprecise estimation of threshold points such as A'.

The first alternative hypothesis of unconditional convergence can be represented by expected the asset recursion function $f_2(A_t)$. This would be consistent with a structural poverty trap if B** lies below the poverty line. The second alternative hypothesis, conditional asset convergence, would imply one such function for each exogenously determined subgroup. In the analysis below subgroup membership is defined by caste, landowning class, location of the household or its education level. Figure 1 illustrates the case of two subgroups. One follows $f_2(A_t)$ while the other is on trajectory $f_3(A_t)$ with each function having its own distinct dynamic accumulation path and asset equilibrium. As a result, in the conditional convergence case poverty traps could be subgroup specific.

Even in the absence of multiple equilibria and poverty traps, there may be a case for helping the poor escape poverty through redistributive policies that i) benefit them in the form of immediate transfers and ii) raise mean asset levels in subsequent periods. We can express future mean asset holdings as a function of households' current assets. If this function is strictly concave, as indicated by $f_2(A_t)$ and $f_3(A_t)$ in Figure 1, then future mean assets are a strictly quasi-concave function of households' current assets. Therefore, reducing current asset inequality would increase mean future asset levels (Aghion *et al.* 1999; Banerjee and Duflo 2003).

Again, this would imply that redistribution can support poverty reduction if the gains for the poor from redistribution are larger than any potential negative effects on economic growth. Testing for concavity of the recursion diagram using household data is therefore a micro-level test analogous to the test for the effects of inequality on economic growth in the cross-sectional macro literature (for a summary see Banerjee and Duflo (2003)).

Finally, it is worth noting that none of the above theories consider the speed of adjustment back to equilibrium as that is ultimately an empirical question. The models can only assume that households are 'temporarily' away from their respective stable dynamic equilibria (A* and A** in the case of multiple dynamic equilibria, B* and/or B** for unconditional and club convergence). This temporary deviation would be due to shocks causing asset losses or gains. Of course, in reality, depending on the speed of adjustment, this temporary state could be unacceptably long and justify policy intervention.

3 The Empirical Literature on Modeling Welfare Dynamics

Compared to the well-developed theoretical literature on welfare dynamics there is a relative dearth of empirical studies. The paucity of this literature is primarily due to the lack of suitable household panel data, but also to the empirical difficulties involved in modeling household welfare dynamics.

In terms of estimation methods the few existing studies have modeled household welfare dynamics either fully parametrically or nonparametrically. Parametrically, the level of household welfare in one period can be approximated by a P^{th} order polynomial function of welfare in the previous period:

$$W_{it} = \alpha_0 + \sum_{p=1}^{P} \alpha_p W_{it-1}^{p} + \beta X_{it} + \varepsilon_{it} \quad (t = 2,...,T)$$

where W_{it} represents household i's welfare at time t, and X_{it} are other household characteristics. Existing studies have limited themselves to a first order autoregression model. While longer lags could affect the dynamic welfare path, they also reduce the number of usable observations and use up degrees of freedom in the estimation.

Three published studies have used a model of this form. Two use the flow variables income and consumption to measure household welfare, the third is based on the stock variable of household asset holdings. Each measure has advantages and drawbacks for analyzing welfare dynamics. The beginning of section 5 explains why I chose household assets as the welfare measure in this paper.

For Hungary and Russia, Lokshin and Ravallion (2004) estimate a third degree polynomial in income levels. They correct for serially dependent error terms and for sample attrition by running T-1 simultaneous autoregressive income equations for the T panel years, instrumenting for initial period income, and simultaneously estimating a Probit attrition model. Jalan and Ravallion (2004) use a fixed effect model in differences for rural China. Using income rather than asset data, neither of these two studies finds evidence for multiple dynamic equilibria. Both papers conclude that current income is a slightly concave function of lagged income. Therefore, poorer households would take longer to adjust to an income shock and are expected to move towards the single equilibrium more slowly than richer households. In contrast, Barrett *et al.* (2006) use asset data from Northern Kenya to estimate changes in assets as a fourth degree polynomial function of past assets, controlling for household and time specific effects. They detect nonlinear asset dynamics with one unstable threshold point and two stable equilibria suggesting the existence of dynamic poverty traps.

One key problem with such parametric specifications is that if the unstable threshold points lie in an area with few observations, which the theories reviewed in the last section suggest, we need a large enough sample size that the fitted polynomial function can accurately reflect the few observations around the thresholds. If the sample size is too small the observations near the threshold point may not be picked up by the polynomial, but instead enter as heteroskedastic and positively autocorrelated error (Barrett 2005). Also, while high order polynomial functions present a way to adjust the coefficients so that in the centre of the domain the function exhibits the desired nonlinearities, they can make the function move around wildly towards in the tails of the distribution. This is to be expected from statistical theory (Hastie *et al.* 2001) and indeed is what Barrett *et al.* (2006) find in practice.

Three studies have tried to address these problems by using nonparametric estimation techniques. For Northern Kenya Barrett *et al.* (2006) run locally linear nonparametric LOWESS regressions of current herd size on its three month lagged value. Lybbert *et al.* (2004) run the same type of nonparametric regressions but on one and ten year lagged herd size in Southern Ethiopia. Adato *et al.* (2006) analyze household asset dynamics in South Africa using local regression methods.[1]

The advantage of nonparametric estimation is that it allows a fully flexible functional form, which is more responsive to potential non-linearities in the asset dynamics. The

[1] Their exact regression method is not specified.

main drawback is that nonparametric techniques suffer from the ‘curse of dimensionality’. That is, the required sample size for estimation grows exponentially with the number of regressors. With common survey sample sizes this means that it is generally only possible to use one explanatory variable in nonparametric regressions. The Barrett *et al.* and Lybbert *et al.* papers are able circumvent this limitation as livestock accounts for almost all household assets in their settings. Hence, it is legitimate to use livestock as the single asset variable. Different types of livestock were aggregated by converting them into Tropical Livestock Units based on metabolic weight.

In settings with more complicated household asset holdings, alternative techniques have to be used. One option is to reduce the number of asset variables by creating an asset index. For some of their survey sites Barrett *et al.* (2006) have done this using a methodology based on factor analysis methods used in Sahn and Stifel (2000). Adato *et al.* (2006) construct an asset index based on asset weights from an estimated livelihood function, which is estimated using a polynomial expansion of basic assets as regressors. Regardless of how assets were aggregated, all three studies using nonparametric techniques have found evidence for asset poverty traps.

Clearly, both estimation techniques used in the existing literature have limitations. Polynomial parametric techniques don’t perform well with few observations around potential inflexion points. Nonparametric estimation is constrained in practice by how much it can control for other variables. Statistically, these two techniques mark the two extremes of the trade-off between the flexibility of the functional form and the ability to control for other covariates. Semiparametric techniques combine the advantages of parametric and nonparametric estimation and seem more suitable for modeling household welfare dynamics. This paper introduces such a technique in section 6.

4 The Data

The data are taken from the International Crop Research Institute for the Semi-arid Tropics' (ICRISAT) Village Level Studies (VLS). The original first generation data (VLS1) was collected for the ten cropping years from 1975/76 to 1984/85. The cropping year runs from July to June. Here, I will refer to each year by the starting year only, that is, 1975 stands for the cropping year 1975/76. Collection of the second generation data (VLS2) started in July 2001 and is ongoing. The data released to date and used for analysis in this paper includes the year 2003.

The VLS1 data collection covered up to 10 villages in three states and a total of 400 households; the VLS2 spans 6 of those villages in two states containing some 265 households. The analysis in this paper is based on a subsample of these data selected on two main criteria. First, a household had to be included in both VLS1 and VLS2. This allows the construction of the longest possible panel spanning a period of 27 years. Second, income information had to be available for all years. This limits analysis to three villages: Aurepalle in the Mahbubnagar district of Andhra Pradesh, Shirapur in the Sholapur district of Maharashtra, and Kanzara in the Akola district of Maharashtra. This subsample contains 886 observations for 72 households with either 12 or 13 observations per household.[2]

[2] Some households are not included in all VLS2 rounds.

Between VLS1 and VLS2 there has been some attrition as some households dissolved, while some others left the villages. Out of the 104 continuously surveyed household in VLS1, 72 could be included in the VLS2 sample. Ideally, we should try to control for the probability of attrition econometrically. This is only defensible if there is a variable in the survey that influences whether or not a household was resurveyed in VLS2 but which does not impact household income. However, the VLS was conceived primarily as an agricultural production survey. Hence, its module on household composition and characteristics is relatively small and does not contain any variables that can credibly identify the attrition probability (such as the place of birth, or the place of residence of relatives). The downside of not being able to control for attrition is that the results may not be representative for the villages. The attrition bias is likely to come from either end of the distribution: better-off and more educated households are more likely to migrate, while poorer households are more likely to disband, die off entirely, or merge with other households. A common factor in explaining attrition in other panels is the age of the household head. However, there is no reason to believe that the age factor affects household attrition differently for different wealth levels. Moreover, as Alderman *et al.* (2001) and Falaris (2003) show, even high levels of attrition in developing country panel surveys often do not affect the consistency of estimation. The upside of using only the continuously observed households is that the subsample containing these 72 households is a balanced panel. Thus, there is no further attrition bias during the period of analysis.

The VLS survey contains detailed information on key assets such as land, and agricultural and financial assets. Information on household composition and education is less detailed, but available at the basic level. The key feature that makes the ICRISAT VLS data suitable for exploring is the length of the panel. This is useful in two ways. First, the long time-span covered by the panels makes it suitable to track changes in assets which, absent any short term shocks, tend to be slow and may not be detectable in shorter panels. Second, unlike the few other panel datasets which cover similarly long periods[3] the VLS data have up to 13 observations per household. With that number it begins to be possible to estimate household specific asset dynamic curves using fixed effects.

There is a 17-year gap between the last year of data VLS1 (1984) and the start of VLS2 (2001). There are different ways this can be handled. I annualized the change over this 17-year period to create a quasi-one-year period and use this in the asset dynamics analysis below.[4]

As a measure of material well-being I use household income rather than consumption. Although the permanent income hypothesis suggests that in theory consumption is a preferable measure of the economic standard of living, two key factors favor the use of income in the case of the VLS data. First, unlike consumption, income data are available for all years and all households. And second, there are reliability concerns regarding consumption data in the early years of data collection (Walker and Ryan 1990).

The VLS data collection was originally stratified into four equal sized landholding classes: landless laborer households and small, medium and large landowning households. The exact cut off points in acres between the landholding classes differ slightly between villages but is around 2.5 acres for small and 5.5 acres for medium

[3] For example, the Chilean data set by Scott with one observation in 1968 and another in 1986
[4] As a robustness check for this crude annualization I repeated the analysis dropping the 1984-2001 period altogether. The results did not change significantly. Thus, everything reported below uses the annualized data for 1984-2001.

landowners.[5] This information on landholding classes is used both in the regression analysis as well as to analyze asset dynamics by subgroup.

Caste membership is an important determinant both for the initial level of household well-being as well as for opportunities for economic advancement. For information on household caste membership I use Ryan's caste rank index (Walker and Ryan 1990) which classifies all castes into one of four groups with caste rank 1 containing the highest castes. Having four caste ranks reduces the number of necessary dummies in the subsequent regressions and makes the analysis of asset dynamics by subgroups more tractable.

Other variables are more standard and include household size, age of and years of education completed by the household head, and the number of working age adults and the number of children in the household. Variables are adjusted for household size and expressed in per adult equivalent terms[6] whenever appropriate. The construction of the asset index and the choice of variables used to construct this index are described in the next section.

5 Constructing the Asset Index

In this paper I use a definition of household welfare and poverty based on the stock variable asset holdings rather than a flow variable such as income or consumption. I focus on assets for three reasons. First, the economic well-being of a household is

[5] For more information on variable definition and on sampling procedures see Singh *et al.* (1985) and Walker and Ryan (1990)

[6] The adult equivalence scale was taken from (Ryan *et al.* 1984) who count men as 1 adult equivalent, women as 0.9 and children under 12 as 0.39 adult equivalents. In this paper I follow the VLS data standard and define children as anyone below 14. As a result the adult equivalent conversions using the Ryan *et al.* is incorrect for anyone aged 12 and 13.

dependent on its stock of assets. From a dynamic perspective it is the accumulation of assets which over time enables households to earn enough income to move out of poverty.[7] This makes an asset-based measure of household welfare more suitable for forward-looking policy design. Second, asset levels fluctuate less from day to day than income and, thus, are closer to the measure of structural well-being that is ultimately of interest to forward looking policy design. Assets can be interpreted as measuring the underlying structural well-being of a household whereas income, and to a lesser extent consumption, contains a much larger amount of stochastic variation (Carter and May 2001). Third, surveys tend to measure asset holdings more accurately than income or consumption. It is easier for a household to recall, and for enumerators to verify, how much X it has than how much it spent on Y or received in payment over the last fourteen days.

Unlike income or consumption, assets are multidimensional. Thus, before we can analyze asset dynamics we first need to summarize assets into an asset index. For parametric analysis such a summary index is convenient as it avoids having to specify a system of simultaneous interrelated autoregressions. For nonparametric and semiparametric analysis reducing assets into a single unidimensional asset index circumvents the curse of dimensionality and, thus, makes estimation possible with the smaller sample sizes commonly found in household survey data.

The asset index is constructed through a livelihood regression (Adato *et al.* 2006) which expresses household well-being as a function of household characteristics and asset holdings. The fitted values of this regression can be interpreted as a asset index

[7] Productivity and technologies and relative terms of trade are equally critical for a household's escape from poverty, but technologies and terms of trade are not state variables of the same sort as assets.

in which assets are weighted according to their marginal contribution to household i's well-being.

The asset index was constructed as follows. Let household i's subsistence need be the product of household size in adult equivalent units and the poverty line, and denote it by S_i. Further, let ℓ_{it} be a measure of i's livelihood at time t, expressed as the ratio of its real income y_{it} to its subsistence need: $\ell_{it} = y_{it} / S_{it}$. Hence, ℓ_{it} measures a household's well-being in poverty line units (PLUs). This provides an intuitive normalization for ℓ_{it} and, hence, the asset index: A measure of 1 means that a household survives on an adult equivalent income right at the poverty line; while $\ell_{it} < 1$ and $\ell_{it} > 1$ indicate poor and non-poor households, respectively. Household i's livelihood in PLUs can be expressed as

$$\ell_{it} = \alpha + \sum_{j=1}^{J} \beta_j \left(\mathbf{A}_{it}, \mathbf{C}_{it} \right) A_{itj} + \sum_{s=1}^{S} \gamma_s \left(\mathbf{A}_{it}, \mathbf{C}_{it} \right) C_{its} + \sum_{t=2}^{T} \delta_t T_t + U_i + \varepsilon_{it} \qquad (1)$$

where $U_i \sim_{iid} N\left(0, \sigma_u^2\right)$. A_{itj} and C_{its} are the j^{th} of J assets and the s^{th} of S household characteristics that contribute to i's livelihood at t. $\mathbf{A}_{it}$ and $\mathbf{C}_{it}$ are control vectors representing household assets and characteristics, and T_t are T-1 year dummy variables. Coefficients $\beta_j \left(\mathbf{A}_{it}, \mathbf{C}_{it} \right)$ represent asset j's marginal contribution to the livelihood. The parentheses indicate that the coefficients depend on all of household i's assets and characteristics at time t.

The fitted values yield the estimated household asset indices and are given by

$$\hat{\ell}_{it} = \hat{\alpha} + \sum_{j=1}^{J} \hat{\beta}_j \left(\mathbf{A}_{it}, \mathbf{C}_{it} \right) A_{itj} + \sum_{s=1}^{S} \hat{\gamma}_s \left(\mathbf{A}_{it}, \mathbf{C}_{it} \right) C_{its} + \sum_{t=2}^{T} \hat{\delta}_t T_t + U_i \qquad (2)$$

To estimate equation 1 we need to construct ℓ_{it}, which in turn requires setting a poverty line. The 1993 Expert Group of the Government of India suggested 49 Rupees per month in 1973/74 prices, which is around Rs630 per year per capita in 1975/76 prices. However, this would classify close to 90 percent of villagers as poor, including many households that would not be regarded as poor in the villages. Instead, I follow recent work by Badiani *et al.* (2007) and use a lower cut off point of 500 Rupees in 1975/76 prices as the poverty line.

Equation 1 was estimated using a random effects panel model using a second-order polynomial expansion of all assets and household characteristics. A random effects model is preferred for two reasons: First, a Hausman test against the fixed effects model did not reject the null hypothesis that the coefficients are the same. The probability that the critical χ^2 value with 74 degrees of freedom is greater than the observed χ^2 of 23.41 is equal to one. Second, the fixed effects specification explained only 65% of the variation in ℓ_{it}, compared to 74% for the random effects model; and the primary objective for the livelihood regression is to project the household asset index as precisely as possible.

The flexible second-order expansion for equation 2 allows the marginal returns to vary both with their own levels as well as with the levels of the other included asset and control variables. The estimation of equation 1 is based on the subsample of 72 continuous households. The subsequent asset dynamics analysis is, therefore, not affected by attrition though it may suffer from some selection bias.[8]

[8] The subsequent analysis and results are based on the asset index constructed by random effects using the subsample of 72 continuous households. I also estimated equation 1 by OLS and using the whole sample of 102 continuous and non-continuous households. This yielded a total four different household asset index estimates. The asset dynamics analysis using the three other asset indices (OLS all

The choice of explanatory variables was informed by the categories of assets identified in the livelihoods literature (see, e.g., Moser and Felton (2007)) and spans physical, productive, financial, natural and human capital.[9] Specifically, the asset vector A_i includes net financial assets, the value of houses, residential plots, productive equipment and consumer durables, acreage of dry and irrigated land owned, the number of bullocks and other bovine livestock owned. The household characteristics vector C_i contains the age and education of the household head, the household size in adult equivalent units[10] and the number of working age adults to proxy the labor endowment of the household. With the exception of the age and education of the household head, all variables were expressed per adult equivalent. To center the curvature of the polynomial at the sample mean, all asset and household characteristics variables and their squares and interaction terms were demeaned. Further, all variables expressed in Rupees, including the poverty line, were converted to real 1975/76 Rupees using the state-specific Consumer Price Index for Agricultural Laborers from Indiastat.

The main objective of this regression is to derive a set of weights to reliably project expected household well-being given its assets holdings. The focus of this regression is, therefore, less on the actual estimated coefficients but on the overall explanatory power. The regression has a good fit and can explain about three quarters of the variation in the household well-being as shown by an R-squared of 0.74. These results provide a solid justification for using the fitted values from equation 2 as the

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households, OLS continuous households and RE all households) produced substantively similar asset indices and asset dynamics results. The estimation results for all four specifications of equation 1 are given in the Appendix.

[9] The VLS does not provide sufficient detail on social capital.

[10] Strictly speaking I used the subsistence need which is equal to household size multiplied by the poverty line.

household asset index. Full results for the estimates of equation 1 are provided in the Appendix.

Figure 2 plots the asset index on the vertical axis against its one-year lagged value on the horizontal axis. The asset index ranges from 0 to 23 PLU, with only 12 observations above 12 PLU. The data points are scattered fairly closely to the 45 degree line. This suggests a low level of asset mobility and is a priori evidence against nonlinear asset dynamics and multiple dynamic equilibria. This simple plot is consistent with overall economic stasis in these three rural villages.

The constant from equation 1 is around 2, suggesting that the average level of household well-being for a household without assets is around twice the poverty line. The median household PLU for VLS1 (1975/6-1984/5) is around 1.5 and for VLS2 (2001/02-2003/4) is around 3.2. The relatively high average level of well-being is partially a result of four factors: First and foremost, household incomes far exceed consumption levels in the VLS. While there is no conclusive explanation for this, it is likely due to an underestimation of consumption levels (Townsend 1994; Morduch 2004). As a consequence, the magnitude of the regression constant of household PLU estimates is consistent with widespread consumption poverty headcounts of 76 percent for VLS1 and 22 percent for VLS2 (Badiani *et al.* 2007). Second, the period over which households have been observed is long. Thus, while average annual growth in assets is low at 0.8%, and consistent with economic stagnation, over almost thirty years this does represent significant compounded growth and has resulted in much higher income and asset holdings in VLS2. Third, due to the regression-to-the-mean effect, the fitted values of the asset index span a smaller range than the observed ℓ_{it}.

This results in fewer projected poor households. Fourth, the Rs 500 poverty line is lower than in some existing papers.

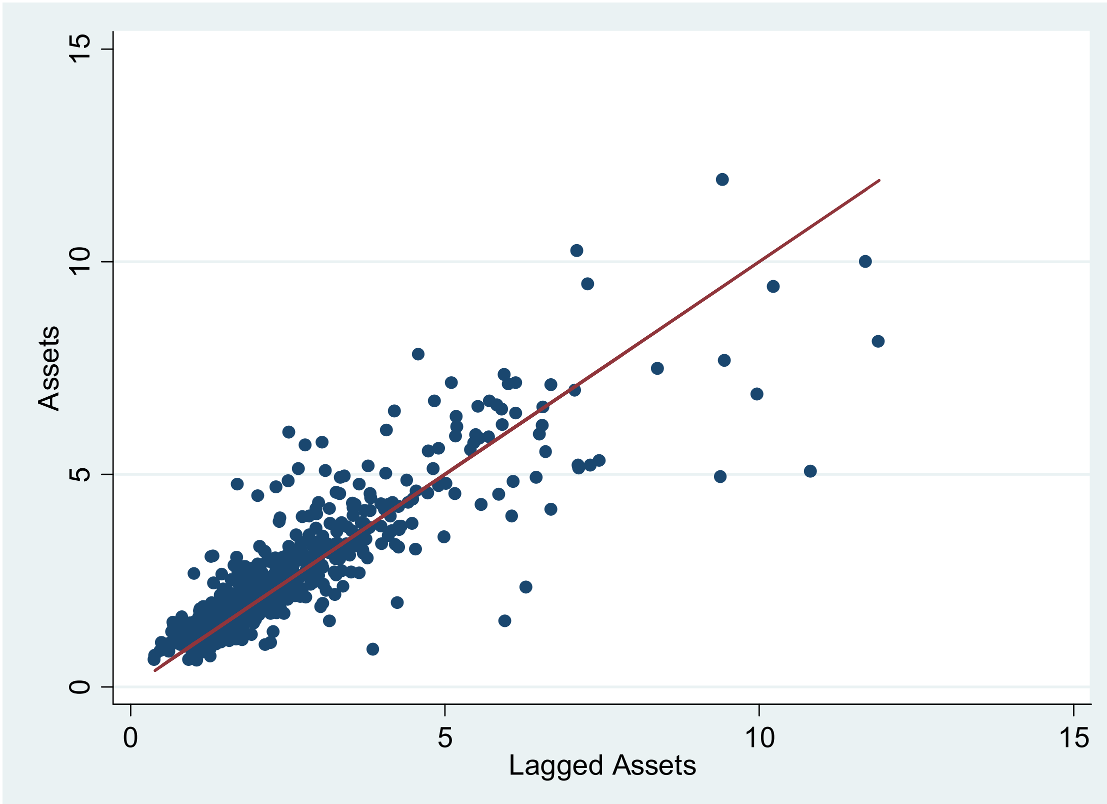

Figure 2 Scatterplot of Asset index against Lagged Asset Index (One year lag)

6 Econometric Methods

Nonparametric Methods

Simple univariate nonparametric regression is equivalent to fitting a smooth function through a scatterplot without any assumptions on the functional form. Its two key assumptions are that the function to be estimated, *f*, is "smooth" and that the covariates are uncorrelated with the error, which is normally and identically distributed with an expected value of zero. Let A_{it} represent household *i*'s asset index at time t then dynamic autoregression of household assets can be written as

$$\begin{aligned} A_{it} &= f(A_{it-1}) + \varepsilon_{it} \\ \varepsilon_{it} &\sim_{iid} N(0, \sigma_\varepsilon^2) \end{aligned} \tag{3}$$

Equation 3 can be estimated using a number of different nonparametric techniques. The analysis below applies locally weighted scatterplot smoothers (LOWESS), local polynomial regressions, and median and natural splines and penalized splines.

LOWESS estimation (Cleveland *et al.* 1988) is a type of local regression and is used to identify dynamic asset equilibria in Lybbert *et al.* (2004) and Barrett *et al.* (2006). It estimates *n* weighted local regressions[11] at each data point A_{it-1} based on only the points in the neighborhood of A_{it-1}. The neighborhoods are defined as a proportion of the total number of observations. The regression weights for each local regression are based on a kernel function and vary inversely with distance from A_{it-1}. A wider bandwidth results in a smoother function and lower variance, but a larger bias. A narrower bandwidth improves bias and tracks the data more closely, but increases variance. The conditional expectation $E[A_{it}]$ is then given by the prediction of the local weighted regression at each value of A_{it-1}.

Kernel weighted polynomial regressions are a related form of local regressions. They differ from LOWESS in that the local regression neighborhood is not defined as a proportion of the total number of observations, but as the set of observations that lie within a specified range of A_{it-1}. In principle both types of local regression support the use of local polynomials, although in practice studies have used locally linear LOWESS only. Polynomial specifications are preferable, however, as the locally

[11] Most commonly these local regressions are linear.

linear estimations tend to be biased in the regions of the distribution where the function has curvature, as it is ‘trimming the hills and filling the valleys’ (Hastie *et al.* 2001). This bias can affect the estimates of the dynamic asset equilibria since these are likely to lie in areas of curvature. Locally linear estimation tends to be preferable for extrapolation outside the sample, as it has reduced bias at the boundaries. Higher order polynomials, in contrast, tend to reduce bias in the interior of the distribution (Hastie *et al.* 2001) though at the cost of increased variance. A priori local polynomials should perform better at fitting the recursive asset relationship.

Another way of estimating equation 3 is through splines. Compared to global polynomial regressions, splines are better at fitting highly curved data (Schumaker 1981; de Boor 2002). The cubic spline is the most popular spline in applications as it offers the best trade-off between goodness of fit and too much local variation. The main drawback is that it is difficult to implement if we have more than one explanatory variable (Pagan and Ullah 1999). In the nonparametric autoregression in equation 3 this is not a problem.

A modification to regular cubic splines are natural cubic splines. These add the additional constraint that the function is linear beyond the lowest and the highest knot[12], freeing up two degrees of freedom at each end of the domain (Hastie *et al.* 2001). These can be used instead to specify more knots in the interior, thus enabling better fit in the interior of the dynamic asset function. Hence, if the asset equilibria lie some way from the boundaries, then statistical theory suggests that natural cubic splines should be preferable to cubic splines. Due to the additional linearity constraints

[12] A spline regression estimates different slopes for different ranges of the independent variable. The endpoints of each subsection of the range is called a knot. More specifically, a knot is the value of κ corresponding to the function $\left(x-\kappa\right)_+$ (see, e.g., equation 5).

the natural cubic splines have more bias, but less variance near the boundaries. The tradeoff between regular and natural splines, and hence between bias and variance in the tails of the distribution, echoes the problems of the global polynomial estimations, which also tend to oscillate wildly in the tails of the distribution.

Another method for estimating the univariate nonparametric model is the penalized spline. This method is borrowed from the statistics literature (Ruppert *et al.* 2003; Wand *et al.* 2005) and has not yet been used in economic applications. It is laid out here in some detail as it forms the basis of the new semiparametric panel data estimator introduced in section 6.3. Equation 3 can be expressed as a penalized spline as follows: [13]

$$\begin{gathered} \mathrm{A}_{it} = \alpha + \beta \mathrm{A}_{it-1} + \sum_{k=1}^{K} u_k \left(\mathrm{A}_{it-1} - \kappa_k \right)_{+} + \varepsilon_{it} \\ 1 \leq i \leq N, 2 \leq t \leq T \end{gathered} \tag{4}$$

where $\varepsilon_{it} \sim N(0, \sigma_{\varepsilon}^{2})$, κ represents a knot, K is the total number of knots, T is the total number of time periods in the panel data, and the plus subscript $_{+}$ indicates that the term $\mathrm{A}_{it-1} - \kappa_k$ only enters the regression if $\mathrm{A}_{it-1} > \kappa_k$. Define

[13] The representation of the penalized spline in equation 4 uses a truncated polynomial basis function. The truncation is included via the '+' terms, i.e., $\left(\mathrm{A}_{it-1} - \kappa \right)_{+}$ is only included if $\mathrm{A}_{it-1} > \kappa$. These basis functions are more intuitive as they resemble regular least squares regression except for the added truncation terms. Actual estimations were carried out using radial cubic thin plate functions, $\mathrm{A}_{it} = \beta_0 + \beta_1 \mathrm{A}_{it-1} + \sum_{k=1}^{K} u_k \left| \mathrm{A}_{it-1} - \kappa_k \right|^{3} + \varepsilon_i$, as these tend to be more computationally stable and give very similar results (Ruppert *et al.* 2003).

$$\boldsymbol{\beta} = \left[\alpha, \beta\right]', \quad \mathbf{X} = \begin{bmatrix} 1 & \mathrm{A}_{11} \\ \vdots & \vdots \\ \vdots & \mathrm{A}_{1t} \\ \vdots & \vdots \\ \vdots & \mathrm{A}_{n1} \\ \vdots & \vdots \\ 1 & \mathrm{A}_{nt} \end{bmatrix}, \; \mathbf{Z} = \begin{bmatrix} (\mathrm{A}_{11} - \kappa_1)_+ & \cdots & (\mathrm{A}_{11} - \kappa_K)_+ \\ \vdots & \ddots & \vdots \\ (\mathrm{A}_{1t} - \kappa_1)_+ & \cdots & (\mathrm{A}_{1t} - \kappa_K)_+ \\ \vdots & \ddots & \vdots \\ (\mathrm{A}_{n1} - \kappa_1)_+ & \cdots & (\mathrm{A}_{n1} - \kappa_K)_+ \\ \vdots & \ddots & \vdots \\ (\mathrm{A}_{nt} - \kappa_1)_+ & \cdots & (\mathrm{A}_{nt} - \kappa_K)_+ \end{bmatrix}, \text{ and} \tag{5}$$

$$\mathbf{u} \equiv \left[u_1, \ldots, u_K\right]' \sim N(0, \sigma_u^2)$$

If we treat **u** as a random effect with $\mathrm{Cov}(\mathbf{u}) = \sigma_u^2\mathbf{I}$ then the penalized spline from equation 4 can be estimated as the best linear unbiased estimator of the mixed model in equation 6.

$$\begin{gathered} \mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{Z}\mathbf{u} + \boldsymbol{\varepsilon} \\ \mathrm{Cov}\begin{bmatrix} \mathbf{u} \\ \boldsymbol{\varepsilon} \end{bmatrix} = \begin{bmatrix} \sigma_u^2\mathbf{I} & \mathbf{0} \\ \mathbf{0} & \sigma_\varepsilon^2\mathbf{I} \end{bmatrix} \end{gathered} \tag{6}$$

Let $\mathbf{C} = \left[\mathbf{X}\ \mathbf{Z}\right]$, then the fitted value vector for equation 6 is

$$\hat{\mathbf{y}} = \mathbf{C}(\mathbf{C}'\mathbf{C} + \boldsymbol{\lambda}^2\mathbf{D})^{-1}\mathbf{C}'\mathbf{y} \tag{7}$$

where, $\mathbf{D} = diag\left(0, \ldots, 0, \mathbf{1}_{Kx1}\right)$ and $\lambda^2 = \left(\sigma_\varepsilon^2 / \sigma_u^2\right)$.

The smoothing parameter λ smoothes the estimated function by penalizing the knot coefficients u_k and can be estimated by restricted maximum likelihood (REML). Define $\mathbf{V} = \sigma_u^2\mathbf{Z}\mathbf{Z}' + \sigma_\varepsilon^2\mathbf{I}$. Then the residual likelihood is

$$\ell_R(\mathbf{V}) = -\frac{1}{2}\Big[n\log(2\pi) + \log\left|\mathbf{V}\right| + \log\left|\mathbf{X}'\mathbf{V}^{-1}\mathbf{X}\right| + y'\mathbf{V}^{-1}\left\{\mathbf{I} - \mathbf{X}(\mathbf{X}'\mathbf{V}^{-1}\mathbf{X})^{-1}\mathbf{X}'\mathbf{V}^{-1}\right\}\mathbf{y}\Big] \tag{8}$$

The estimator for λ is then the ratio of the estimated fixed and random variance components:

$$\hat{\lambda}^2_{REML} = \left(\hat{\sigma}^2_{\varepsilon,REML} / \hat{\sigma}^2_{u,REML}\right) \tag{9}$$

$\hat{\mathbf{y}}$ in equation 6 is then an estimated best linear unbiased predictor (Ruppert *et al.* 2003). The degrees of freedom used in fitting equation 7 measure the degree of non-linearity in the estimated function with larger degrees of freedom indicating a more non-linear function.

In actual applications penalized splines also have a distinct advantage compared to regular splines estimators. Their estimation results are very insensitive to the choice of knots (French *et al.* 2001; Ruppert 2002). Penalized splines also have at least four advantages over non-spline smoothers. First, they represent a model-based approach to smoothing based on statistical principles of maximum likelihood and prediction. Second, they can be implemented using mixed model software. Third, the mixed model representation means that the smoothing parameter λ can be chosen automatically from the data through REML. And fourth, the mixed model framework allows inference via standard likelihood ratio tests.

Parametric Methods

Following existing parametric studies (Jalan and Ravallion 2004; Barrett *et al.* 2006), the parametric global polynomial regressions estimate the change in the asset index as a function of the P^{th}-order polynomial of the lagged asset index. A cubic function is the lowest order polynomial that can detect multiple stable dynamic equilibria as it allows the curvature of the function to switch. Since Jalan and Ravallion (2004) use this specification I have included it in the estimations below for comparison purposes. In the presence of multiple dynamic equilibria, however, a cubic function has a tendency to force the stable equilibria into the tails of the distribution. The analysis below, therefore, also includes a fourth degree polynomial which provides additional flexibility [although it, too, can suffer from oversmoothing (Barrett *et al.* 2006)].

The change in the asset index is estimated as

$$\begin{gathered}\Delta \mathrm{A}_{it} = \sum_{p=1}^{P} \alpha_p \mathrm{A}_{it-1}^{p} + \mathbf{X}_{it}\beta + \sum_{t=3}^{T} \gamma_t T_t + U_i + \varepsilon_{it} \\ 1 \le i \le N,\ 2 \le t \le T, \varepsilon_{it} \sim N(0, \sigma_{\varepsilon}^{2})\end{gathered} \tag{10}$$

where ΔA_{it} is the change in household i's asset index between years t and $t\text{-}1$, $\boldsymbol{X}_{it}$ is a Cx1 vector of control variables, where C is the number of control variables, the T_t's are time dummies, and U_i controls for either household fixed effects or, if we can assume $U_i \sim_{iid} \mathrm{N}\left(0, \sigma_u^2\right)$, a random household intercept.[14] Using the changes in household assets as the dependent variable explicitly estimates growth rates and also controls for time invariant household unobservables.

[14] Section 7 shows that the random effects specification of equation 10 is appropriate.

In the analysis below vector $\boldsymbol{X}_{it}$ contains the following time-varying control variables: The age of the household head and its square control for life-cycle effects. Similarly, household size and its square control for economies of scale; and years of education of the household head and its square account for returns to human capital. The number of adults and its square and the number of children and its square control for available household labor and dependents, respectively. Also included in $\boldsymbol{X}_{it}$ are the two time-invariant household characteristics caste and landholding class. Continuous variables, their squares and interaction terms are demeaned to generate an exact second-order local approximation at the sample mean. Where appropriate variables are used in per adult equivalent terms.

Semiparametric Methods

Semiparametric methods contain a combination of nonparametric and parametric components. They combine an unknown functional form for some variables with unknown finite-dimensional parameters. A simple semiparametric model is the partially linear model (PLM). It imposes no parametric conditions on the asset autoregression function, but allows linear control for other covariates. We can estimate asset dynamics as

$$\begin{gathered} \mathrm{A}_{it} = \alpha + \mathbf{X}_{it}\beta + \sum_{t=3}^{T} \gamma_t T_t + f(A_{it-1}) + \varepsilon_{it} \\ 1 \le i \le N,\ 2 \le t \le T, \varepsilon_{it} \sim N(0, \sigma_\varepsilon^2) \end{gathered} \tag{11}$$

where $\boldsymbol{X}_{it}$ and all T_t enter the model linearly, and the relationship between assets and lagged assets is estimated nonparametrically. $\boldsymbol{X}_{it}$ contains the same control variables as in the parametric model in equation 10.

As long as the lag structure in our asset autoregression is shorter than the total length of the panel then each household enters the estimation more than once. The rural Indian data have 13 observations per household. Thus, using one year lags in the autoregression each household is represented 12 times.

The non- and semiparametric estimators in equations 6 and 11 do not use the panel information. Penalized splines, unlike other scatterplot smoothers, are easily extendable to panel data models and can exploit the additional information we have from longitudinal data. Analogously to the global parametric model in equation 10 we can extend the semiparametric model from equation 11 by a random household intercept (Ruppert *et al.* 2003).

Consider the extended partially linear mixed model

$$\begin{gathered} \mathrm{A}_{it} = \alpha + U_i + f\left(\mathrm{A}_{it-1}\right) + \mathbf{X}_{it}\beta + \sum_{t=3}^{T} \gamma_t T_t + \varepsilon_{it} \\ 1 \le i \le N,\ 2 \le t \le T,\ U_i \sim_{iid} \mathrm{N}\left(0, \sigma_u^2\right), \varepsilon_{it} \sim N(0, \sigma_\varepsilon^2) \end{gathered} \tag{12}$$

where T_t is a time dummy equal to one at time t and zero otherwise that accounts for time specific effects.[15] Again we assume that f is smooth. If U_i is a random household intercept we can estimate equation 12 using a mixed model representation of the penalized spline. Let

[15] The first time dummy is T_3 for the following reason. Since we are estimating a first order autoregression, the first observation for each household is at t=2. If we then omit the time dummy associated with this observation, i.e., T_2, to represent the base period, the first included time dummy is T_3. Similarly, the first included time dummy for the three year lag estimations is T_5.

$$
\mathbf{X}=\begin{bmatrix}
1 & A_{11} & X_{111} & \cdots & X_{11C} & T_3 & \cdots & T_{T-1} \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
1 & A_{1t} & X_{1t1} & \vdots & X_{1tC} & \vdots & \vdots & \vdots \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
1 & A_{n1} & X_{n11} & \vdots & X_{n1C} & \vdots & \vdots & \vdots \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
1 & A_{nt} & X_{nt1} & \cdots & X_{ntC} & T_3 & \cdots & T_{T-1}
\end{bmatrix},
$$

$$
\mathbf{Z}_{RE}=\begin{bmatrix}
0 & \cdots & 0 & (A_{11}-\kappa_1)_+ & \cdots & (A_{11}-\kappa_K)_+ \\
\vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\
0 & \cdots & 0 & (A_{1t}-\kappa_1)_+ & \cdots & (A_{1t}-\kappa_K)_+ \\
1 & \cdots & 0 & (A_{21}-\kappa_1)_+ & \cdots & (A_{21}-\kappa_K)_+ \\
\vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\
1 & \cdots & 0 & (A_{2t}-\kappa_1)_+ & \cdots & (A_{2t}-\kappa_K)_+ \\
\vdots & \cdots & \vdots & \vdots & \ddots & \vdots \\
0 & \cdots & 1 & (A_{n1}-\kappa_1)_+ & \cdots & (A_{n1}-\kappa_K)_+ \\
\vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\
0 & \cdots & 1 & (A_{nt}-\kappa_1)_+ & \cdots & (A_{nt}-\kappa_K)_+
\end{bmatrix} \tag{13}
$$

$$
\text{and } \mathbf{u}=\left[U_1,\ldots,U_K,u_1,\ldots,u_K\right]'
$$

Then we can estimate 12 using the following mixed model

$$
\mathbf{y}=\mathbf{X}\boldsymbol{\beta}+\mathbf{Z}_{RE}\mathbf{u}+\boldsymbol{\varepsilon}
$$

$$
\mathrm{Cov}\begin{bmatrix}\mathbf{u}\\ \boldsymbol{\varepsilon}\end{bmatrix}=\begin{bmatrix}\sigma_U^2\mathbf{I} & \mathbf{0} & \mathbf{0}\\ \mathbf{0} & \sigma_u^2\mathbf{I} & \mathbf{0}\\ \mathbf{0} & \mathbf{0} & \sigma_\varepsilon^2\mathbf{I}\end{bmatrix} \tag{14}
$$

$\sigma_U^2\mathbf{I}$ measures the variation between households, $\sigma_\varepsilon^2\mathbf{I}$ measures the within household variation, and $\sigma_u^2\mathbf{I}$ controls the amount of smoothing used to estimate *f*. The partially linear model estimated by a mixed model representation of penalized splines combines the advantages of the global parametric model with the flexible functional form of a fully nonparametric model.

The random effects semiparametric penalized splines model in equation 12 was estimated using the *R* package SemiPar (Wand *et al.* 2005) which estimates the smoothing parameter λ through restricted maximum likelihood (REML), and cross checked using the model-selection-based algorithm in Ruppert et al. (2003: Appendix B).

Alternatively, we can use the mixed model representation of the penalized spline to estimate a fixed effects model. To control for unobserved household heterogeneity in the estimation of household asset dynamics we can let U_i from equation 12 be non-random and instead represent a household fixed effect, yielding

$$\begin{gathered} \mathrm{A}_{it} = \alpha + U_i + f\left(\mathrm{A}_{it-1}\right) + \mathbf{X}_{it}\beta + \sum_{t=3}^{T}\gamma_t T_t + \varepsilon_{it} \\ 1 \le i \le N,\ 2 \le t \le T,\ \ \varepsilon_{it} \sim N(0, \sigma_\varepsilon^2) \end{gathered} \tag{15}$$

Equation 15 can be estimated similar to equation 12. We only need to redefine the fixed and random components of the mixes model by moving the zero-one submatrix of household intercepts from the random component matrix **Z** to the fixed component matrix **X**. Let

$$
\mathbf{X}_{FE} = \begin{bmatrix}
0 & \cdots & 0 & \mathrm{A}_{11} & X_{111} & \cdots & X_{11C} & T_3 & \cdots & T_{T-1} \\
\vdots & \ddots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
0 & \cdots & 0 & \mathrm{A}_{1t} & X_{1t1} & \vdots & X_{1tC} & \vdots & \vdots & \vdots \\
1 & \cdots & 0 & \mathrm{A}_{21} & X_{211} & \vdots & X_{21C} & \vdots & \vdots & \vdots \\
\vdots & \ddots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
1 & \cdots & 0 & \mathrm{A}_{2t} & X_{2t1} & \vdots & X_{2tC} & \vdots & \vdots & \vdots \\
\vdots & \cdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
0 & \cdots & 1 & \mathrm{A}_{n1} & X_{n11} & \vdots & X_{n1C} & \vdots & \vdots & \vdots \\
\vdots & \ddots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
0 & \cdots & 1 & \mathrm{A}_{nt} & X_{n11} & \cdots & X_{ntC} & T_3 & \cdots & T_{T-1}
\end{bmatrix}, \tag{16}
$$

$$
\mathbf{Z} = \begin{bmatrix}
(\mathrm{A}_{11}-\kappa_1)_+ & \cdots & (\mathrm{A}_{11}-\kappa_K)_+ \\
\vdots & \ddots & \vdots \\
(\mathrm{A}_{1t}-\kappa_1)_+ & \cdots & (\mathrm{A}_{1t}-\kappa_K)_+ \\
\vdots & \ddots & \vdots \\
(\mathrm{A}_{n1}-\kappa_1)_+ & \cdots & (\mathrm{A}_{n1}-\kappa_K)_+ \\
\vdots & \ddots & \vdots \\
(\mathrm{A}_{nt}-\kappa_1)_+ & \cdots & (\mathrm{A}_{nt}-\kappa_K)_+
\end{bmatrix}
$$

$$
\text{and } \mathbf{u} \equiv [u_1,...,u_K]' \sim N(0,\sigma_u^2)
$$

Then we can estimate 15 using the following mixed model

$$
\mathbf{y} = \mathbf{X}_{FE}\boldsymbol{\beta} + \mathbf{Z}\mathbf{u} + \boldsymbol{\varepsilon}
$$
$$
\mathrm{Cov}\begin{bmatrix} \mathbf{u} \\ \boldsymbol{\varepsilon} \end{bmatrix} = \begin{bmatrix} \sigma_u^2\mathbf{I} & \mathbf{0} \\ \mathbf{0} & \sigma_\varepsilon^2\mathbf{I} \end{bmatrix} \tag{17}
$$

$\sigma_\varepsilon^2\mathbf{I}$ measures the within household variation, and $\sigma_u^2\mathbf{I}$ controls the amount of smoothing used to estimate *f*. The estimator of the fixed effects mixed model representation of the penalized splines is also implemented in *R* and builds on the model-selection based algorithm in Ruppert et al. (2003: Appendix B).

7 Results

Table 1 reports the estimated dynamics pattern and location of stable dynamic equilibria for each of the estimation techniques introduced in section 6. The point estimates for all techniques and lag structures find only a single dynamic asset equilibrium for the rural Indian households and identify a very similar shape for the asset dynamics. However, there are significant differences across techniques in the estimated asset equilibrium levels and in the size of the confidence intervals. Thus, even in the context of economic stasis in the three rural Indian village the estimation technique matters with the semiparametric random effects model providing the most precise estimates.

Overall, asset accumulation for the VLS households is very slow, if it happens at all. As illustrated by the scatter plot in Figure 2 and as borne out by the recursion diagrams below, the VLS villages represent a stagnant economy. Households have a strong to tendency remain at their level of asset holdings and well-being.

The ranges reported in Table 1 indicate the estimated dynamic asset accumulation path follows the 45 degree line very closely. In the first two columns the low and high values in brackets, respectively, show where the lower and upper 95 percent confidence bands cross the diagonal. The bracketed numbers, therefore, provide the 95 percent confidence interval for the asset equilibrium. For the fully parametric techniques, in particular, the confidence intervals span most of the asset index range, e.g., between 0.5 and 9.5 for the fourth degree polynomial on the one year lagged data. In other words, we cannot reject the null hypothesis that, in expectation, no household's wealth changes from one year to the next. This represents a random walk along the 45 degree line and suggests a very strong case of economic stagnation. The third and fourth columns in Table 1 reinforce this by presenting the share of household observations that fall within the confidence interval of the dynamic asset equilibrium.

The confidence intervals for the nonparametric penalized splines are smaller, but still very large at between 3 and 9 poverty line units. By controlling for covariates as well as allowing for flexible asset dynamics, the semiparametric penalized splines allow greater precision in the estimates. The confidence intervals for the dynamic asset equilibrium shrink to between 2.4 and 4.1 PLUs. However, this greater statistical significance does not detract from the economically significant result of very slow asset accumulation and overall economic stagnation for the VLS households, as even for the semiparametric techniques the asset estimated dynamic accumulation path still follows the 45 degree line very closely (see Figure 5).

Since household asset holdings in the VLS villages are fairly stagnant and the resulting asset accumulation path are close to linear, the choice of estimation technique matters little in identifying the shape of asset dynamics. However, the precision of the point estimates seems to benefit from simultaneously allowing for flexible modeling of the asset autoregression and controlling for household characteristics, location, and time.

The asset recursion diagrams for the various nonparametric estimation techniques look substantively similar in that they all follow the 45 degree line closely. Representative for the various techniques, Figure 3 shows the estimated recursion diagram for equation 4 using penalized splines. The central red line displays the estimated asset accumulation path and the grey areas above and below the curve show the 95 percent confidence bands. The rug plot at the bottom of the graph depicts the density of the observations.

Table 1 Summary of Asset Equilibria Estimates by Estimation Technique and Lag Structure

	Approximate Location of Stable Equilibrium (in PLUs)		*% of observations in 95% Confidence Interval of the Stable Equilibrium*	
	1 year lags	3 year lags	1 year lags	3 year lags
Nonparametric Regression				
LOWESS (bandwidth = 0.4)	1.8-4.2	1.5-5.2	35%	48%
Kernel weighted local cubic regression (bandwidth = 2)	2-9	2-6.5	39%	36%
Median Cubic Spline	1.8-3.5	1.9-3.8	31%	30%
Natural Cubic Spline	1.8-6.7	1.8-4.1	42%	34%
Penalized Spline (Equation 6)	7.1 [3,9]	5.7 [4.4,6.3]	21%	6%
Penalized Spline RE	7 [3.6,9]	5.8 [5.4,6.2]	13%	2%
Global Parametric Regression				
4th order Polynomial RE (Equation 10)	5 [0.5,9.5]	5 [1.2, 13]	94%	70%
3rd order Polynomial RE (Equation 10)	6.2 [1,12]	4.4 [0,11]	78%	98%
Semiparametric Regression				
PLM Penalized Spline (Equation 11)	2.8 [2.5,3.6]	3.1 [2.4,4.1]	16%	21%
PLMM Penalized Spline RE (Equation 14)	2.8 [2.7,3.3]	3.2 [2.7,4.1]	9%	15%
PLMM Penalized Spline FE (Equation 17)	1.7, 6.3 [0,8]	5.8 [0,12]	96%	98%

- Asset Index estimated by Equation 1 using random effects.
- In each cell the line above the brackets indicates a single crossing point or its range.
- Ranges in brackets indicate where confidence bands overlap 45 degree line

The relative linearity of the estimated asset recursion function is also reflected in the approximately 3.25 degrees of freedom used by the penalized spline in fitting the nonparametric function $f(A_{it-1})$. This implies that households' dynamic asset accumulation paths are close to linear.

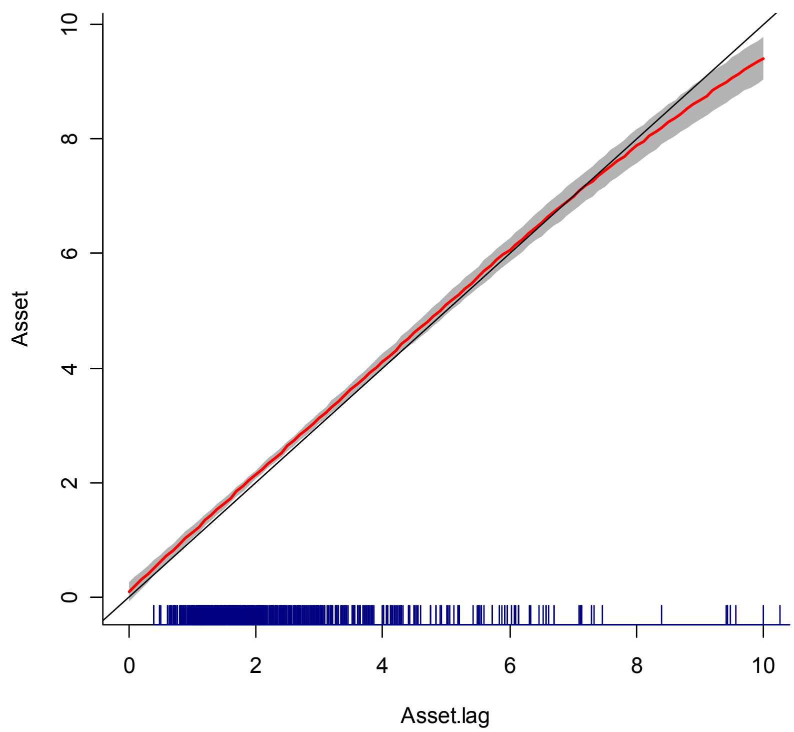

Figure 3 Assets vs. Lagged Assets (Nonparametric Penalized Splines) One year lag

The nonparametric penalized spline estimations are robust to changes in the specification. Using a different spline basis, for example using truncated polynomial spline bases linearly or quadratically instead of cubic thin plate spline bases, causes very small changes in the estimated dynamic asset path. The asset recursion diagrams are similarly unaffected for relatively large changes in the smoothing parameter λ. For example, specifying 20 degrees of freedom, instead of the 3.25 degrees of freedom estimated by REML, lets the penalized spline estimator follow the data more closely. However, the estimated recursion diagram hardly changes, again likely due to the relatively linear nature of the true dynamic asset path we are trying to estimate.

This robust result is confirmed through the LOWESS and kernel weighted local polynomial regression estimates. They, too, are unaffected over a large range of bandwidths. Again, this is unsurprising given the almost linear shape of the asset recursion function. In practice, the asset dynamic path almost coinciding with the 45 degree line means that on average households do not move much from their initial asset position signifying an extremely low level of year-on-year asset mobility in the three villages.

For the global polynomial parametric regression we first need to identify the appropriate specification for equation 10. We can reject the hypothesis that equation 10 has a single intercept through the Breusch Pagan LM test. The probability that the chi-square test statistic is larger than the 95 percent critical value for one degree of freedom is 0.004. Hence, we should use a panel data model.

Next, we can test the random effects assumption of no correlation between unobserved household heterogeneity, u_i, and the other right hand side variables through a Hausman test of the consistent fixed effects model against the potentially inconsistent random effects model. The probability that the test's chi-squared statistic is greater than the 95 percent critical value is 0.17. Thus, we can use the more efficient random effects estimator which allows us to keep the time invariant regressors caste, landholding class and education in the model.

Table 2 summarizes the global parametric regression results for the third and fourth order polynomial specifications for one-year and three-year asset lag structure. Within each lag structure the results differ between the fourth and the third order polynomial specification, i.e., comparing column (1) with (2) and column (3) with (4). Similarly, the lag structure leads to different coefficient estimates, i.e., comparing column (1) with (3) and column (2) with (4). However, few of the coefficients are statistically significant and all regressions explain less than 30 percent of the variation.

Table 2 Global Polynomial Asset Dynamics Regressions (Random Effects)

Dependent Variable: Change in Asset Index

	(1)	(2)	(3)	(4)
	One year lags		**Three year lags**	
	4th order polynomial	3rd order polynomial	4th order polynomial	3rd order polynomial
lagged asset index	0.101	-0.561	-1.339	-0.199
	(0.562)	(0.006)**	(0.002)**	(0.057)
lagged asset index squared	-0.111	0.072	0.328	-0.048
	(0.005)**	(0.046)*	(0.036)*	(0.087)
lagged asset index cubed	0.013	-0.004	-0.039	0.004
	(0.001)**	(0.008)**	(0.065)	(0.000)**
lagged asset index to the fourth power	-0.000		0.002	
	(0.000)**		(0.062)	
household size (in adult equivalents)	-0.964	-0.981	-0.511	-0.562
	(0.007)**	(0.020)*	(0.178)	(0.245)
squared Household size (in adult equivalents)	-1.137	-1.391	-2.740	-2.609
	(0.443)	(0.311)	(0.109)	(0.174)
age of HH head	-0.023	0.093	0.212	0.024
	(0.964)	(0.879)	(0.789)	(0.972)
squared age of HH head	-1.175	-1.820	-6.351	-5.458
	(0.513)	(0.142)	(0.070)	(0.075)
years of education HH head	0.279	0.336	0.534	0.469
	(0.112)	(0.067)	(0.007)**	(0.026)*
squared years of education HH head	-0.354	-0.433	-0.109	-0.048
	(0.585)	(0.529)	(0.779)	(0.924)
# of working age adults per AE	1.374	1.176	0.776	0.470
	(0.234)	(0.366)	(0.259)	(0.531)
squared # of working age adults per AE	0.357	0.542	0.860	0.967
	(0.632)	(0.527)	(0.021)*	(0.040)*
# of children per AE	0.404	0.283	0.027	-0.064
	(0.422)	(0.616)	(0.932)	(0.859)

Table 2 (Continued)

squared # of children per AE	0.062	0.041	0.522	0.458
	(0.552)	(0.650)	(0.056)	(0.004)**
Constant	0.389	0.943	1.691	0.825
	(0.123)	(0.000)**	(0.000)**	(0.000)**
R-Squared	0.2875	0.2764	0.2938	0.2631
Observations	741	741	597	597
Number of unique HH id	72	72	72	72

Robust p values in parentheses
* significant at 5%; ** significant at 1%
Landownership class, caste, time and village dummies are included in the regression, but not reported here for brevity.

To examine the economic significance of the regression results we need to plot the asset recursion diagrams. To translate these regression coefficients of the lagged asset variables into the asset recursion diagram I predict the dependent variable 'change in asset index' and then add the lagged asset index. This gives the predicted asset index, which is plotted against the lagged index as the inner red line in Figure 4 for the one year lag structure from column (1). The outer green lines show the 95% confidence bands. The asset recursion diagrams for the third order polynomial estimates and for both polynomials for the three year lags have an almost identical shape and are therefore omitted for brevity. In all four recursion diagrams the 95 percent confidence bands include the 45 degree line for most of the range. The point estimates for the single stable dynamic equilibria all lie between 4.4. and 6, as shown in Table 1, but the given the wide confidence bands these point estimates are at best indicative.

The semiparametric penalized splines models produce asset recursions diagrams with the lowest dynamic equilibria of all the estimation techniques: between 2.8 PLUs for the one year lags and 3.1 PLUs for the three year lags. To put these levels into perspective, the median household PLU level for 2001 was 3.1, suggesting that the median household had already reached its dynamic equilibrium at around three times the poverty line income, which translates into around Rs1500 per adult equivalent. For the reasons outlined at the end of section 5, this estimate is likely on the high side. For comparison, in 2001 22 percent of households still lived below the low consumption poverty line of Rs500 (Badiani *et al.* 2007).

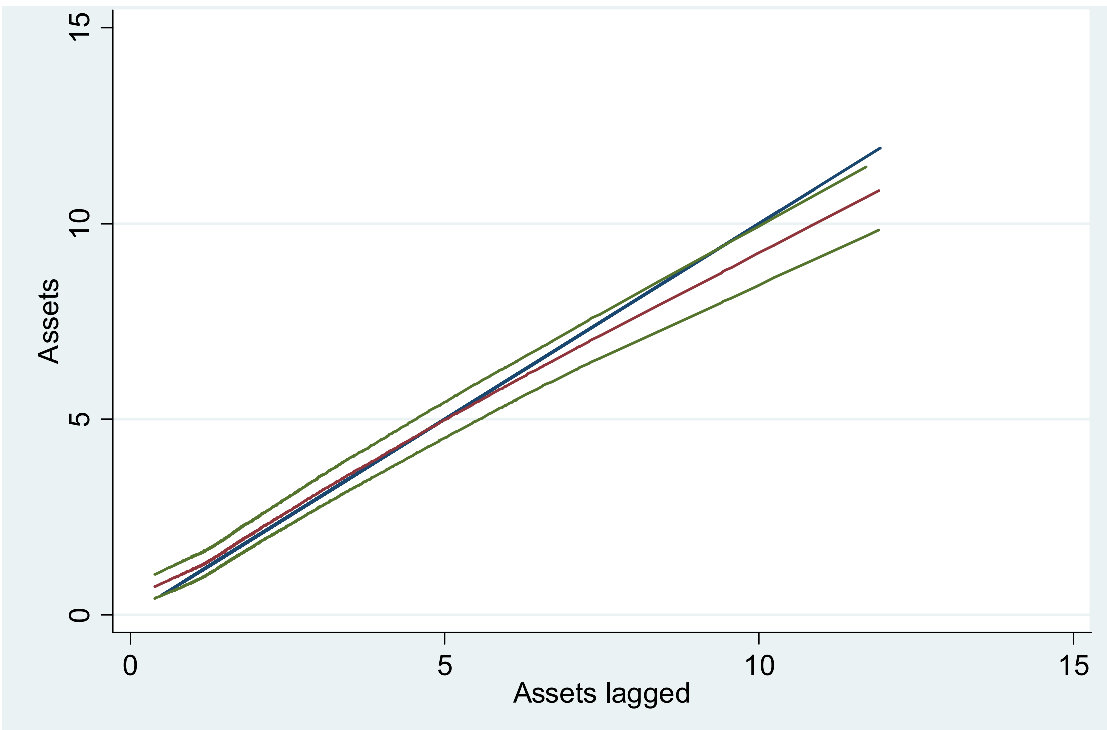

Figure 4 Assets vs. Lagged Assets (4th order Global Parametric Estimation) One year lag

The simple semiparametric partial linear model from equation 11 and the semiparametric partially linear mixed model with the added random intercept from equation 12 yield very similar results and produce the tightest confidence bands of all the estimation techniques. Adding the random effects shrinks the confidence bands a little bit more resulting in the asset recursion diagram in Figure 5. This suggests that the partially linear model random effects model specification is the preferred specification for modeling asset poverty dynamics in the three villages.

The non-linear components use up only slightly over 1 degree of freedom as the estimated asset dynamics path is almost perfectly linear. The slopes from the semiparametric models are slightly smaller than for the other techniques, suggesting a somewhat faster, though still slow, process of asset accumulation.

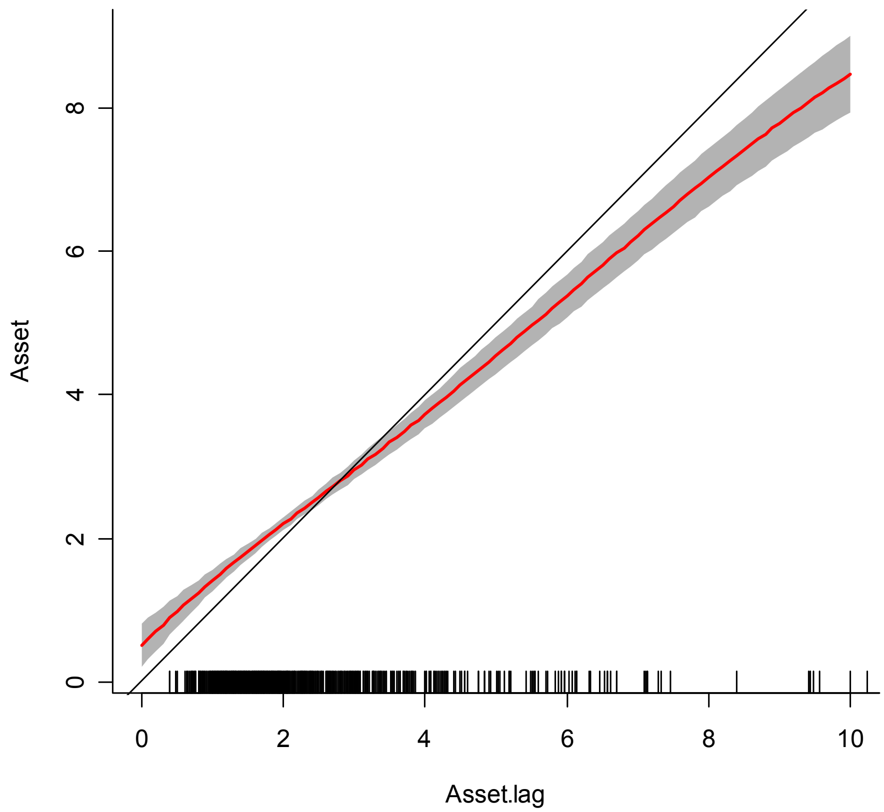

Figure 5 Semiparametric Estimation of Assets vs. Asset Lagged (Penalized Splines Random Effects) One year lag

In addition to the above analysis of the asset dynamics for the whole sample of households we can estimate asset dynamics and equilibria by subpopulation. Table 3 summarizes the results by village, caste rank, landholding class and education based on the semiparametric penalized splines estimation with random effects. All subgroups share a similar pattern for their estimated dynamic asset accumulation path. The shape of this pattern resembles that of the full sample discussed above and is characterized by a single dynamic asset equilibrium and a dynamic path that is relatively linear and close to the 45 degree line. The subgroups differ primarily in the location of their equilibria.

Among the three villages, Aurepalle has the highest dynamic asset equilibrium point estimate followed by Kanzara and Shirapur. The difference between Aurepalle and Shirapur is also statistically significant as their 95 percent confidence intervals do not overlap. This is consistent with the finding that income growth in the Andhra Pradesh village Aurepalle has outperformed the Maharahstra villages (Badiani *et al.* 2007) and suggests that economic growth in Aurepalle has managed to sustainably raise the level of structural well-being as indicated by a higher asset equilibrium.

The analysis by caste confirms the expectation that higher castes enjoy higher asset equilibria. The relationship between caste rank and the level of the stable equilibrium is monotone. However, the differences in dynamic equilibria are not statistically significant across caste ranks as evidenced by the overlapping confidence intervals in Table 3. This is due to a combination of heterogeneity within caste ranks and relatively small sample sizes for each caste rank.

Similarly, among landowning households, greater acreage systematically increases the level of the asset equilibrium. Large landowners enjoy statistically significantly higher asset holdings. The differences between the other groups are not statistically

Table 3 Stable Dynamic Asset Equilibria by Subgroups

	Number of observations	*Approximate Location of Stable Equilibrium (in poverty line units)* Semiparametric Penalized Splines (Random Effects)
By Village		
Aurepalle	286	4.4 [3,7]
Shirapur	338	2.5 [2.2,2.8]
Kanzara	312	3.5 [3,4.5]
By Caste Rank		
1 (highest)	260	4.2 [2.7,5.9]
2	195	3 [2.4,6.3]
3	247	2.5 [2.2,2.9]
4 (lowest)	234	2.1 [2,12]
By Landholding		
Landless	246	2.8 [2.5,3.5]
Small Landholders	265	2.5 [2.2,3.2]
Medium Landholders	206	3.3 [2.9,3.7]
Large Landholders	219	4.5 [4,7]
By Education		
No Education	544	2.2 [2,2.8]
Up to 4 years	204	4 [3,6]
More than 4 years	188	3 [2.5,5.5] and [7,15]*

- Asset Index estimated by equation 1 using random effects.
- * indicates that the equilibrium is driven by very few observations
- In each cell the line above the brackets indicates a single crossing point or its range.
- Ranges in brackets indicate where confidence bands overlap 45 degree line

significant, again probably due to heterogeneity within landholding classes and due to small subsamples. Landless households have a slightly higher equilibrium than smallholders, but this is likely caused by shopkeepers and civil servants being included in the landless category.

Splitting the sample by education level of the household head we see that education raises the expected asset equilibrium level. The difference in dynamic equilibria betweenhouseholds with uneducated heads and those with up to 4 years of education is statistically significant. The highest education category has two equilibria. The one at around 3 PLU is likely driven by the larger number of household heads that have 5 or 6 years of education, thus, hardly more than the 'up to 4 years' group. The other, very high equilibrium is probably driven by the few household heads that have tertiary education.

I also tested the robustness of the above results against two alternative explanations of why we only see one dynamic asset equilibrium. First, social sharing rules may mean that any gains in assets by one household are at least partly distributed via its social networks. Alternatively, household composition may be endogenous. If a household manages to accumulate assets it also attracts people currently living outside of it to join the household. Both of these mechanisms would result in a household that is above the dynamic equilibrium to move back to it over time. We can test for these alternative explanations by re-estimating the livelihoods function in equation 1 but using total household income rather than household income adjusted by household subsistence needs as the dependent variable. This asset index then reflects any additional assets gained by the household, whether or not their returns were consumed by the (original) household members. Redoing the analysis with this asset index did not substantively change the asset recursion diagrams. This suggests that social sharing rules and endogenous household composition do not affect the asset accumulation path. This mirrors the results of similar analysis for rural Pakistan and Ethiopia (Naschold 2006).

A second reason why we might not see multiple equilibria is that the time period between observations is only one year. If total asset holdings change slowly, this may be too short an interval to pick up the long run asset dynamics. Indeed, the existing studies which have found multiple asset equilibria have either used longer spells [five year in South Africa (Adato *et al.* 2006) and thirteen years in Western Kenya (Barrett *et al.* 2006)], or are based only on pastoralists' livestock holdings, which are much more volatile than other asset holdings [see (Barrett *et al.* 2006) on Northern Kenya] or both [see (Lybbert *et al.* 2004) on Southern Ethiopia].

Rerunning the above analysis with a longer, three-year asset index lag did not substantively change the results. The asset recursions diagrams continue to show a single dynamic equilibrium at a level very similar to the one year lags. Again, this confirms the results for Pakistan and Ethiopia in Naschold (2006).

Finally there are two other possible, but untestable, explanations as to why the data do not show bifurcating welfare dynamics. First, evidence from Ethiopia (Santos and Barrett 2006) has shown that bifurcating equilibrium paths may depend on the quality of the growing season. When years are good all farmers expect to be on concave accumulation path. In contrast, in mediocre years only some farmers, including probably the experienced, expect to grow, whereas others expect to fall behind. In the VLS data we can partially control for good and bad growing years using information on the rainfall pattern. However, it appears that asset dynamics in the VLS data are not substantively different for good and bad harvest years, though this may be a result of rainfall being a crude measure for the quality of the growing season.

Second, the VLS covers poor rural populations. Close to 90 percent would fall under the poverty line recommended by the 1993 Expert Group of the Government of India. It is, therefore, possible that in the country as a whole there are additional higher asset equilibria, which are absent from the VLS data, as the VLS villages contain very few richer households. The only way to test for this would be to use a data set that is more representative of India as a whole. If indeed there were higher equilibria in other rural or urban parts of the country, then the findings in this paper could be interpreted as geographic poverty traps in the sense that there may be unique low level equilibria for the rural villages of the VLS.

8 Conclusions

This paper has modeled household asset dynamics and asset thresholds in three villages in rural semi-arid India. It used nonparametric and parametric estimation techniques from the existing literature and adapted a new (to economics) semiparametric panel data method adapted from the statistics literature. This method can flexibly model the asset accumulation process while controlling for household characteristics and location and time. It can accommodate random intercepts and was extended to handle household fixed effects. The empirical results for all methods paint a picture of economic stasis in these villages.

The theoretical literature on household welfare dynamics and most of the empirical case studies have focused on modeling the shape of the dynamic welfare path, in particular the existence of multiple dynamic equilibria and welfare thresholds. This is an important area of research as it can contribute to the design of more effective anti-poverty policies and, indeed, is what motivated the improved semiparametric estimation technique in this paper. However, the empirical investigation of rural India showed clearly that in practice welfare dynamics can look very different from those hypothesized in the models. The three rural Indian villages are characterized by a *lack* of welfare dynamics. Households asset accumulation is a very slow, almost static process approximating a random walk along the 45 degree line where next period welfare equals this period's.

In this context of economic stasis it is not surprising that the different econometric methods come to qualitatively similar conclusions, as the main advantage of more complex nonlinear modeling techniques is in the context of highly nonlinear dynamics. The process of asset accumulation for these rural households is close to linear in its central tendency. There is no evidence for non-convexities either for the whole sample or any of the subgroups. This suggests that households in the VLS villages do not face an asset poverty trap in the form of multiple dynamic asset equilibria. This does not mean, however, that village households are not trapped in poverty. On the contrary, since in expectation households remain at their initial asset positions, all households with an asset position below the poverty line of 1 PLU are effectively trapped in poverty.

The estimated mean asset accumulation path also shows very little concavity. This has two implications. First, there is no significant difference in the speed of asset accumulation between asset-poor and asset-rich households. And second, reducing asset inequality would only provide direct benefits to the recipients, but would not enhance the overall rate of subsequent asset growth.

Where the results from the different estimation techniques differ is in the precision of their estimates. The parametric techniques resulted in the largest confidence bands encompassing most of the range of the asset data. The semiparametric penalized splines with random effects had the smallest confidence bands and is the preferred model specification. It also displays the lowest asset equilibria at around three times the lowest rural poverty line, or Rs1500 per adult equivalent per year in 1975/76 prices, or close to $2 per day when converted to 1995 PPP $. While this level is well above the poverty line and, therefore, may appear not too low, it is likely to understate the extent of poverty in the villages. Perhaps a better way of interpreting it is in a relative context. The median household in the villages has already achieved the equilibrium level of well-being in 2001 suggesting that absent any changes in the welfare distribution, the concurrent level of consumption poverty of around 22 percent is the long term equilibrium.

In any event, the estimation results, particularly the relatively large parts of the asset range that are spanned by the confidence bands, present a picture of economic stasis. This image is confirmed by the low average annual growth rate in per capita asset holdings over the period 1975 to 2003 of 0.8%. Since the estimated asset accumulation path does not suggest a dynamic way for households to move towards a higher equilibrium, future improvements in welfare will have to come from structural changes that raise the asset equilibrium itself. In terms of social policy, the estimated linear asset dynamics also indicate that the key function for social safety nets is their traditional most basic role of ensuring survival. Since there are no bifurcation points in the form of unstable dynamic equilibria they cannot help to leverage dynamic gains or, conversely, prevent dynamic losses.

When we relax the assumption that households share a common underlying dynamic asset accumulation path and examine asset dynamics by subgroup we find predictable patterns of club convergence with a single equilibrium per subgroup. Higher castes, large landholders and more educated households have monotonically greater asset equilibria than their lower caste, smaller landholder and less educated peers. In addition, recent improvements in economic conditions in Andhra Pradesh village of Aurepalle have resulted in a higher equilibrium level of asset holdings that in the Maharashtra villages.

To put the methods and results into a broader perspective it is worth concluding with some caveats about using an asset index and a single equation model to estimate household welfare dynamics. For policy purposes a key practical issue is how he estimated equilibrium asset index relates back to actual asset holdings. We can of course work back mechanically and use the coefficients from the asset index regressions and do some calibration against commonly held bundles of assets to 'recover' typical asset levels associated with the one asset equilibrium. That would give the average value of all the assets in the index that a household would have in equilibrium, thus creating a 'representative household'. This concept, however, has limited value, as any number of linear combination of assets can yield that same asset index, not just the combination of 'average' assets.

Moreover, there may be economies of scale and of scope in reaching the equilibrium level of assets. That is, there is likely to be limited substitutability, and a considerable degree of complementarity between assets. This makes it difficult to identify which particular assets households below the equilibrium need assistance with; let alone identifying which particular *combination* of assets is required. There is a need to disentangle the effects of different assets. This can be done in two different ways. Either by supplementing quantitative surveys with qualitative data, where particular types of households identified from the quantitative data are revisited and asked further questions about their gains and losses of assets (Adato *et al.* 2006) or, in theory, by extending the statistical analysis beyond a single asset index. Techniques exist to flexibly model multiple assets and interactions of assets on the right hand side of the equation through, for example, additive models and single index models or penalized splines. The practical constraint for such modeling is the availability of data. However, there is another layer of complication. Asset dynamics are an autoregressive process. Thus, if multiple assets and interaction of assets are included on the right hand side, they will need to also appear as the next period's left hand side. And the statistical literature has not yet developed suitable estimation techniques to solve systems of simultaneous non- or semi-parametric equations.

The bottom line is that estimation of household welfare dynamics is currently limited to using a single welfare variable in a single equation autoregression model. In choosing the welfare variable, an asset index has clear advantages over more commonly used income or consumption, notwithstanding the issues identified above. If the aim is to be forward looking and to help inform poverty reduction policies then an asset index is the most appropriate measure of well-being as it captures future expected well-being rather than the particular stochastic income draw observed for a household at the time of the survey.

The most appropriate single equation autoregressive model to identify household welfare dynamics should satisfy three minimum conditions. First, it needs to be able to flexibly model the functional form of the autoregression to allow for possibly non-convexities in any part of the asset range. Second, it must be able to control for other household characteristics, subgroups and time and location specific effects. Third, it obviously needs to be able to handle panel data. The semiparametric mixed model representation of penalized splines including random or fixed effects satisfies these requirements and can be implemented without specialist software. It, therefore, represents one of the most suitable currently available techniques to model household asset poverty dynamics.

APPENDIX

Asset Index Regressions - Dependent Variable: Poverty Line Units

	(1)	(2)	(3)	(4)
	VLS1&2 all obs – OLS Regression	VLS1&2 All obs - Random Effects	VLS1&2 Cont HHs - OLS Regression	VLS1&2 Cont HH - Random Effects
subsistence need per HH in AE at PL income	-0.028	-0.921	0.745	0.615
	(0.981)	(0.385)	(0.610)	(0.648)
squared subsistence need per HH in AE at PL income	0.224	0.806	-1.179	-2.394
	(0.933)	(0.788)	(0.717)	(0.521)
age of HH head	-0.192	0.625	0.267	0.751
	(0.645)	(0.011)*	(0.536)	(0.009)**
squared age of HH head	-6.269	-7.716	-7.729	-7.612
	(0.031)*	(0.000)**	(0.076)	(0.000)**
years of education HH head	0.718	0.619	0.713	0.830
	(0.305)	(0.014)*	(0.055)	(0.000)**
squared years of education HH head	-0.699	0.116	0.473	-0.000
	(0.556)	(0.726)	(0.495)	(0.999)
real net financial assets per AE	2.017	1.140	1.085	1.108
	(0.296)	(0.000)**	(0.226)	(0.063)
squared real net financial assets per AE	1.284	2.486	2.375	2.375
	(0.339)	(0.000)**	(0.001)**	(0.000)**
real house value per AE	2.391	1.177	1.508	1.509
	(0.130)	(0.306)	(0.201)	(0.083)
squared real house value per AE	-0.461	2.220	1.105	1.660
	(0.720)	(0.034)*	(0.002)**	(0.000)**
real equipment value per AE	3.302	4.693	6.139	6.473
	(0.227)	(0.210)	(0.243)	(0.065)
squared real equipment value per AE	-1.679	-7.683	-8.977	-7.315
	(0.103)	(0.214)	(0.401)	(0.430)
real consumer durables value per AE	2.903	1.602	6.556	5.862
	(0.452)	(0.562)	(0.059)	(0.000)**

squared real consumer durables value per AE	6.115	-1.955	-18.333	-17.779
	(0.042)*	(0.798)	(0.047)*	(0.000)**
dry land owned in acres per AE	0.183	0.353	0.208	0.318
	(0.154)	(0.000)**	(0.240)	(0.048)*
squared dry land owned in acres per AE	-0.074	-0.048	0.004	0.001
	(0.283)	(0.028)*	(0.932)	(0.987)
irrigated land owned in acres per AE	1.083	0.869	0.732	0.611
	(0.043)*	(0.001)**	(0.233)	(0.126)
squared irrigated land owned in acres per AE	0.012	-0.027	0.159	0.120
	(0.844)	(0.812)	(0.369)	(0.335)
# bullocks owned per AE	0.193	1.187	1.104	1.210
	(0.780)	(0.000)**	(0.228)	(0.014)*
squared # bullocks owned per AE	1.536	-0.275	0.143	-0.274
	(0.133)	(0.768)	(0.903)	(0.723)
# of other bovine livestock owned per AE	0.242	0.137	0.196	0.171
	(0.208)	(0.258)	(0.564)	(0.550)
squared # of other bovine livestock owned per AE	0.410	0.060	-0.133	-0.083
	(0.002)**	(0.575)	(0.563)	(0.604)
# of working age adults per AE	0.452	0.542	0.801	0.677
	(0.145)	(0.000)**	(0.149)	(0.059)
squared # of working age adults per AE	-0.965	-0.129	0.611	1.466
	(0.072)	(0.847)	(0.641)	(0.329)
edufinassets	0.084	-2.472	-2.135	-2.238
	(0.878)	(0.010)*	(0.270)	(0.144)
eduhouse	2.644	-0.468	3.791	3.029
	(0.374)	(0.815)	(0.002)**	(0.000)**
eduequip	5.068	7.400	2.241	1.574
	(0.103)	(0.000)**	(0.756)	(0.717)
edudurab	-1.793	0.195	5.305	5.725
	(0.753)	(0.836)	(0.258)	(0.035)*
edudryland	1.069	-0.570	-0.666	-0.654
	(0.132)	(0.000)**	(0.039)*	(0.000)**
eduirrland	-0.211	-0.176	-1.222	-0.763
	(0.546)	(0.838)	(0.223)	(0.328)
edubullocks	0.533	-0.168	0.600	-0.072
	(0.590)	(0.850)	(0.483)	(0.928)
edulivestocks	-0.966	-0.323	-0.286	-0.364
	(0.082)	(0.595)	(0.736)	(0.586)

eduadult	0.984	0.677	0.953	0.424
	(0.415)	(0.002)**	(0.697)	(0.823)
finassethouse	-3.768	-9.948	-8.234	-9.084
	(0.165)	(0.000)**	(0.189)	(0.036)*
finassetequip	-2.354	-3.114	-4.707	-1.030
	(0.092)	(0.643)	(0.734)	(0.931)
finassetdurab	-2.267	14.742	18.253	17.590
	(0.785)	(0.000)**	(0.378)	(0.264)
finassetdryland	-1.594	0.803	1.242	1.345
	(0.451)	(0.168)	(0.325)	(0.075)
finassetirrland	-1.533	-1.703	-2.390	-2.634
	(0.173)	(0.196)	(0.314)	(0.107)
finassetbullocks	6.253	2.431	2.391	1.866
	(0.366)	(0.540)	(0.616)	(0.590)
finassetlivestock	-0.925	-1.235	-2.290	-2.273
	(0.381)	(0.000)**	(0.136)	(0.015)*
finassetadult	-15.482	-0.801	-2.469	-2.382
	(0.092)	(0.741)	(0.782)	(0.720)
houseequip	2.467	1.341	-3.862	-6.163
	(0.319)	(0.232)	(0.743)	(0.430)
housedurab	0.000		0.000	
	(.)		(.)	
housedryland	2.011	0.179	0.297	0.022
	(0.426)	(0.816)	(0.682)	(0.967)
houseirrland	-0.808	-2.454	-3.638	-3.327
	(0.245)	(0.000)**	(0.002)**	(0.000)**
housebullocks	-4.496	5.547	7.722	7.890
	(0.427)	(0.010)*	(0.021)*	(0.000)**
houselivestock	0.239	-2.222	-0.837	-0.639
	(0.829)	(0.020)*	(0.665)	(0.705)
houseadult	-0.862	-0.983	0.824	-1.374
	(0.658)	(0.508)	(0.757)	(0.586)
equipdurab	-6.865	16.334	19.638	16.408
	(0.150)	(0.166)	(0.134)	(0.049)*
equipdryland	-2.554	2.039	0.000	-0.371
	(0.055)	(0.189)	(.)	(0.883)
equipirrland	1.643	5.551	0.000	9.023
	(0.047)*	(0.005)**	(.)	(0.000)**
equipbullocks	14.589	-1.726	0.000	
	(0.061)	(0.558)	(.)	
equiplivestock	-3.949	-4.177	-7.107	-6.026
	(0.101)	(0.141)	(0.033)*	(0.000)**
equipadult	-15.027	9.994	24.107	19.339
	(0.163)	(0.261)	(0.310)	(0.306)
durabdryland	0.000		-1.723	
	(.)		(0.692)	
durabirrland	0.000		9.471	
	(.)		(0.021)*	
durabbullocks	0.000		-2.375	-0.967
	(.)		(0.351)	(0.585)
durablivestock	0.000		0.000	
	(.)		(.)	
durabadult	0.000		0.000	
	(.)		(.)	

drylandirrland	0.095	-0.037	0.198	0.205
	(0.723)	(0.820)	(0.610)	(0.448)
drylandbullocks	0.249	0.606	0.885	0.843
	(0.392)	(0.239)	(0.197)	(0.082)
drylandlivestock	-0.286	0.176	0.375	0.301
	(0.246)	(0.219)	(0.112)	(0.014)*
drylandadult	0.381	-0.034	-0.599	-0.403
	(0.431)	(0.783)	(0.178)	(0.250)
irrlandbullocks	-1.265	1.238	0.793	0.621
	(0.443)	(0.000)**	(0.196)	(0.005)**
irrlandlivestock	1.516	0.376	-0.029	0.110
	(0.086)	(0.055)	(0.941)	(0.739)
irrlandadult	1.515	0.440	0.483	1.149
	(0.341)	(0.589)	(0.779)	(0.337)
bullockslivestock	-1.329	-0.403	-0.229	-0.390
	(0.151)	(0.340)	(0.811)	(0.547)
bullocksadult	1.745	-1.478	-2.942	-2.567
	(0.447)	(0.508)	(0.192)	(0.009)**
livestockadult	-2.957	-1.420	-0.262	-0.404
	(0.007)**	(0.100)	(0.837)	(0.687)
year== 1976	0.103	0.080	0.091	0.120
	(0.635)	(0.667)	(0.549)	(0.233)
year== 1977	0.425	0.460	0.510	0.523
	(0.089)	(0.000)**	(0.031)*	(0.000)**
year== 1978	0.383	0.332	0.349	0.346
	(0.169)	(0.139)	(0.065)	(0.000)**
year== 1979	0.313	0.353	0.451	0.461
	(0.199)	(0.045)*	(0.058)	(0.000)**
year== 1980	0.067	0.012	0.112	0.106
	(0.583)	(0.896)	(0.301)	(0.051)
year== 1981	-0.002	0.209	0.458	0.437
	(0.979)	(0.003)**	(0.031)*	(0.000)**
year== 1982	0.375	0.467	0.647	0.620
	(0.021)*	(0.001)**	(0.007)**	(0.000)**
year== 1983	0.406	0.516	0.541	0.542
	(0.058)	(0.000)**	(0.131)	(0.020)*
year== 1984	0.159	0.288	0.280	0.279
	(0.219)	(0.000)**	(0.326)	(0.242)
year== 2001	1.029	1.281	1.163	1.142
	(0.054)	(0.000)**	(0.005)**	(0.000)**
year== 2002	1.448	1.318	1.336	1.281
	(0.043)*	(0.004)**	(0.077)	(0.000)**
year== 2003	1.890	1.533	1.611	1.554
	(0.011)*	(0.000)**	(0.020)*	(0.000)**
Constant	1.961	2.004	2.047	2.116
	(0.015)*	(0.000)**	(0.003)**	(0.000)**
Observations	1836	1357	886	886
R-squared/Overall R-squared	0.69	0.68	0.74	0.74
Number of unique HH id		132		72

Robust p values in parentheses
* significant at 5%; ** significant at 1%

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Chapter 3:
Do Short-Term Observed Income Changes Overstate Structural Economic Mobility?[16]

1 Introduction

Understanding changes in household welfare, i.e., economic mobility, is key for designing poverty reduction policies. In creating effective policy interventions it is especially important to understand to what extent observed changes in household welfare over time are stochastic, for instance resulting from random transitory gains and losses, or structural, for example due to changes in household asset holdings. Short-term stochastic welfare fluctuations suggest a need for stabilizing household incomes, whereas structural transitions reflect predictable changes in household welfare that can inform forward-looking, longer-term poverty reduction policies.

Define total economic mobility as the directional changes in observed household incomes. Then total economic mobility can be decomposed into two components: structural economic mobility due to changes in household assets and characteristics; and stochastic economic mobility due to changes in stochastic transitory (or unearned) income and measurement error. Existing empirical studies of household income dynamics in developing countries use measures of total economic mobility and tend to find considerable changes in incomes over short periods of time. They, thus, conclude that a very large proportion of poor households move in and out of poverty over short periods of time and that only a small proportion is chronically poor. As a result most poverty is classified as transitory (for a good summary of evidence see Baulch and Hoddinott (2000)). Estimates for the transitory proportion of poverty run as high as 74

[16] This chapter was co-authored with Christopher B. Barrett.

percent (Baulch and McCulloch 1998) and 80 percent in rural Pakistan (McCulloch and Baulch 2000) and 88 percent in rural India (Gaiha and Deolalikar 1993).[17]

Such results seem inconsistent with widespread observations of “poverty traps” in rural areas of the developing world which imply limited economic mobility. However, since existing studies do not distinguish between structural and stochastic sources of economic mobility, it is likely that much apparent economic mobility is at least partially explained by random changes in transitory income and measurement error. This would, in turn, lead to an overestimate of short-term, transient poverty and an underestimate of long-term, chronic poverty.

The objective of this paper is to explore whether estimates of (total) economic mobility based on observed incomes are positively correlated with the length of time over which households are observed. We develop a statistical test to indicate whether stochastic income changes matter and, thus, whether there exists a significant difference between total and structural economic mobility. The basic premise of the test is that if transitory income is random, then subsequent transitory income draws ultimately cancel each other out and we should see an inverse relationship between total economic mobility and the length of time over which income changes are measured (the ‘spell length’). Estimates based on short spells of longitudinal data would then suggest more structural mobility than truly exists.

Using household survey data from rural Pakistan as well as Monte Carlo simulations we show that panel data estimates of total household economic mobility and transitory

[17] These high estimates are partly driven by the presence of measurement error in household incomes. However, even partly controlling for measurement error, the transitory component of overall poverty remains large falling only slightly, from 80 to 68 percent, in rural Pakistan (McCulloch and Baulch 2000).

poverty are inversely correlated to the length of time over which households are observed. Since we control for classical measurement error this result is driven primarily by changes in stochastic transitory income. Typical household panel data sets span only a few years and, hence, likely lead to overestimating structural economic mobility and transitory poverty. Our findings offer a partial explanation for the high rates of economic mobility and transitory poverty commonly reported in places widely considered to be economically stagnant or "trapped"; they also highlight the importance of constructing long-running panel data sets for analyzing structural welfare dynamics.

2 Method

Using the definition of total economic mobility from above, we can think of structural changes in household income as due to changes in non-stochastic income resulting from both changes in household assets and changes in returns to these assets; and stochastic changes in household income as resulting from changes in stochastic transitory income as well as changes in measurement error. Let vectors A_{it} and r_t represent household i's assets and returns to asset at t, respectively. Further define ε_{it}^{T} and ε_{it}^{M} to be unobserved transitory income and measurement error, respectively. Assuming measurement error and transitory income are proportional to income, total household income can then be expressed as:

$$y_{it} = A_{it} r_t e^{\varepsilon_{it}^{T}} e^{\varepsilon_{it}^{M}} \qquad (1)$$

Taking logarithms yields

$$\log y_{it} = \log A_{it} + \log r_t + \varepsilon_{it}^T + \varepsilon_{it}^M \tag{2}$$

Let asset returns r_t be stationary and stochastic with a mean return of r and mean zero iid error ε_{it}^R. Then, $r_t = r + \varepsilon_t^R$. Let τ denote the time elapsed between two income observations Taking first differences of equation 2 gives

$$\log y_{it} - \log y_{it-\tau} = \left(\log A_{it} - \log A_{it-\tau}\right) + \left(\log r_t - \log r_{t-\tau}\right) + \left(\varepsilon_{it}^T - \varepsilon_{it-\tau}^T\right) + \left(\varepsilon_{it}^M - \varepsilon_{it-\tau}^M\right) \tag{3}$$

where the second term is just a stochastic intercept. This decomposition shows that total income changes based on survey data overestimate structural economic mobility if there are contemporaneous changes in random transitory income and in stochastic returns on assets. We want to isolate the effect of the change in stochastic components of observed income. Since survey incomes are measured with error and this measurement error can conflate the transitory income effect we need to control for this error to the extent possible. We assume that income suffers from classical measurement error and adjust income accordingly so as to filter out the final term in equation 3 (see the Appendix for details).

Since we want to capture both the direction and the magnitude of household income changes we should measure economic mobility as a directional income change (Fields 2001). Specifically, we choose the change in the logarithm of household income. This appeals both because the difference in log incomes approximates the growth rate in household incomes and because a given absolute change in income is valued more for relatively poorer households, a desirable property when using the economic mobility measure to characterize poverty dynamics. Annualizing the change in logarithmic household income yields the following economic mobility measure.

$$\mathrm{m}_{i(\mathrm{t},\tau)}\left(y_{it}, y_{it-\tau}\right) = \frac{\log y_{it} - \log y_{it-\tau}}{\tau} \tag{4}$$

This ensures that we can compare income changes across different spell lengths. Now let $\overline{y}_t$ be mean adult equivalent household income at *t*, then we can normalize $\mathrm{m}_{i(t,\tau)}$ and define the normalized annual average change in log income per adult equivalent as follows

$$\mathrm{M}_{\mathrm{i},(\mathrm{t},\tau)}\left(y_{it}, y_{it-\tau}, \overline{y}_t, \overline{y}_{t-\tau}\right) = \frac{\mathrm{m}_{\mathrm{i}(\mathrm{t},\tau)}\left(y_{it}, y_{it-\tau}\right)}{\mathrm{m}_{\mathrm{i}(\mathrm{t},\tau)}\left(\overline{y}_t, \overline{y}_{t-\tau}\right)} - 1 \tag{5}$$

This normalization removes the average growth rate in the spell and defines household incomes changes relative to the average log income change. This scaling allows us to compare $\mathrm{M}_{i(t,\tau)}$ measures across years with high and low average income growth rates.[18] At the mean value of income, $\frac{\mathrm{m}_{\mathrm{i}(\mathrm{t},\tau)}\left(y_{it}, y_{it-\tau}\right)}{\mathrm{m}_{\mathrm{i}(\mathrm{t},\tau)}\left(\overline{y}_t, \overline{y}_{t-\tau}\right)}$ equals one and $\mathrm{M}_{i(t,\tau)}$ equals zero, thus the sign of $\mathrm{M}_{i(t,\tau)}$ shows whether a household experienced greater or smaller economic mobility than the mean.

Equation 5 can be used to derive a simple test for the effect of the change in transitory income $\varepsilon_{it}^T - \varepsilon_{it-1}^T$ on $\mathrm{M}_{i(t,\tau)}$. Define the normalized annual average change in log income per adult equivalent for the shortest and longest spells that can be created from a panel dataset as

$$\mathrm{M}_{\text{longest}} = \mathrm{M}_{\mathrm{i},(\mathrm{T},\mathrm{T}-1)}\left(y_{iT}, y_{i1}, \overline{y}_T, \overline{y}_1\right) = \frac{\mathrm{m}_{\mathrm{i}(\mathrm{T},\mathrm{T}\text{-}1)}\left(y_{iT}, y_{i1}\right)}{\mathrm{m}_{\mathrm{i}(\mathrm{T},\mathrm{T}-1)}\left(\overline{y}_T, \overline{y}_1\right)} - 1 \tag{6}$$

[18] This could be extended to control for cross-sectional differences, e.g., due to location or other exogenous household characteristics. We would simply need to construct a different mean income for each subgroup.

$$\mathrm{M}_{\text{shortest}}=\mathrm{M}_{\mathrm{i},(\mathrm{t},1)}\left(y_{it},y_{it-1},\overline{y}_{t},\overline{y}_{t-1}\right)=\frac{\mathrm{m}_{\mathrm{i}(\mathrm{t},1)}\left(y_{it},y_{it-1}\right)}{\mathrm{m}_{\mathrm{i}(\mathrm{t},1)}\left(\overline{y}_{t},\overline{y}_{t-1}\right)}-1\quad\forall t\in\{2,3,...,T\} \tag{7}$$

Then let $f(\mathrm{M}_{\text{shortest}})$ and $f(\mathrm{M}_{\text{longest}})$ denote the associated kernel densities. A first graphical check for the effect of transitory income changes on total income changes is simply to plot $f(\mathrm{M}_{\text{shortest}})$ and $f(\mathrm{M}_{\text{longest}})$ on the same graph. If changes in transitory income are random, and their distribution is independent and stationary, they would cancel each other out over time. Then $f(\mathrm{M}_{\text{longest}})$ would be more peaked and more concentrated around its mean than $f(\mathrm{M}_{\text{shortest}})$, suggesting that there is more variability in short-term income changes. As a result, estimates of total economic mobility and transitory poverty based on short observation spells would be systematically higher than estimates based on longer observation periods, with the difference between the two estimates determined by the size of changes in transitory income relative to changes in total income. Thus, we should expect an inverse monotonic relationship between total economic mobility estimates and the time between panel data observations.

Statistically, we can test for the effect of transitory income on economic mobility as follows. For our purposes comparing the two kernel densities $f(\mathrm{M}_{\text{shortest}})$ and $f(\mathrm{M}_{\text{longest}})$ reduces to testing whether they have the same variance.[19] The distribution of the data determines the appropriate statistical homogeneity of variance test. First, if both kernel densities are normally distributed, then parametric homogeneity of variance tests such as the Levene or Brown-Forsythe tests are most powerful. If at least one kernel density is not normally distributed we need to use nonparametric tests for the homogeneity of

[19] If the two kernel densities have the same variance we would want to test for differences in kurtosis. This paper does not extend the discussion to kurtosis for three reasons. First, variances are found to differ both in the application to data from Pakistan and in the Monte Carlo simulations. Second, with common sample sizes estimates of fourth order moments are likely to be unstable. Third, in the likely case of non-normally distributed $\mathrm{M}_{(t,\tau)}$ we would need non-parametric homogeneity of kurtosis tests which have not yet been developed in the statistical literature.

variance. By construction, $f(M_{shortest})$ and $f(M_{longest})$ have the same mean. However, the choice of nonparametric test depends on whether the two kernel densities also have the same median. This can be verified by the Wilcoxon-Mann-Whitney test. If medians are equal, then the appropriate nonparametric homogeneity of variance tests are Ansari-Bradley and Fligner-Killeen; if not, then we have to resort to a less powerful, omnibus nonparametric test such as Kolmogorov-Smirnov.

The autocorrelation structure of the data is likely to influence the results. Depending on the autocorrelation of transitory income, the stochastic component of total income change in equation 3 can be smaller or larger in the long or in the short spell. Let $\varepsilon_{it}^{T} = \rho\varepsilon_{it-\tau}^{T}$. If ρ=0, i.e., transitory income is independent and identically distributed, we would expect positive and negative transitory incomes to cancel out as the length of the observation period increases. As a result, the ratio of structural to stochastic economic mobility – the signal-to-noise ratio – would be larger for the longer spell and $f(M_{longest})$ should be more centered around its mean than $f(M_{shortest})$. When transitory income is iid our homogeneity of variance test thus represents a conservative lower bound for the effect of transitory income on total economic mobility as even the longer spell will contain some stochastic component.

If $\rho \in (0,1]$ then ε_{it}^{T} depends positively on $\varepsilon_{it-\tau}^{T}$. Such positively autocorrelated transitory income represents the case of cumulative advantage and disadvantage. The relative size of the stochastic component of total income changes falls for all spell lengths as the correlation coefficient gets larger. In other words, $Var\left(M_{i(t,\tau)}\right)$ should fall as ρ increases.

When $\rho \in [-1, 0)$ then ε_{it}^{T} and $\varepsilon_{it-\tau}^{T}$ are negatively correlated and successive transitory income draws cancel each other out. From a modeling perspective this represent a fairly uninteresting case as the effect of transitory income on economic mobility depends not on the length of the observation period but on whether each of these periods are odd or even. Moreover, negative autocorrelation in transitory income seems highly unlikely in any realistic scenario.

Actual survey panel data doesn't allow us to test for the effect of different autocorrelation structures on total economic mobility. Instead, we explore this effect in the next section using Monte Carlo simulation.

3 Results from rural Pakistan data and simulations

The IFPRI Pakistan Rural Household Survey (PRHS) panel contains five years of income data for around 700 households collected between 1986/87 and 1990/91.[20] For each household we constructed four one-year, three two-year, two three-year and one four-year income mobility spells.

The kernel densities of annualized percentage changes in real per capita household log income, $M_{i(t,\tau)}$, for all spell lengths are shown in Figure 6. The relationship between spell length and dispersion is monotonic: The longer the observation spell the more income changes are concentrated around their mean and the smaller the variance. This confirms the hypothesis that, for a given average change in income, total economic mobility is inversely correlated with spell length. In turn, this implies that transitory

[20] The data and detailed documentation is available from IFPRI at http://www.ifpri.org/data/pakistan01.htm.

income changes constitute a larger part of total income changes the shorter the time spanned by the panel.

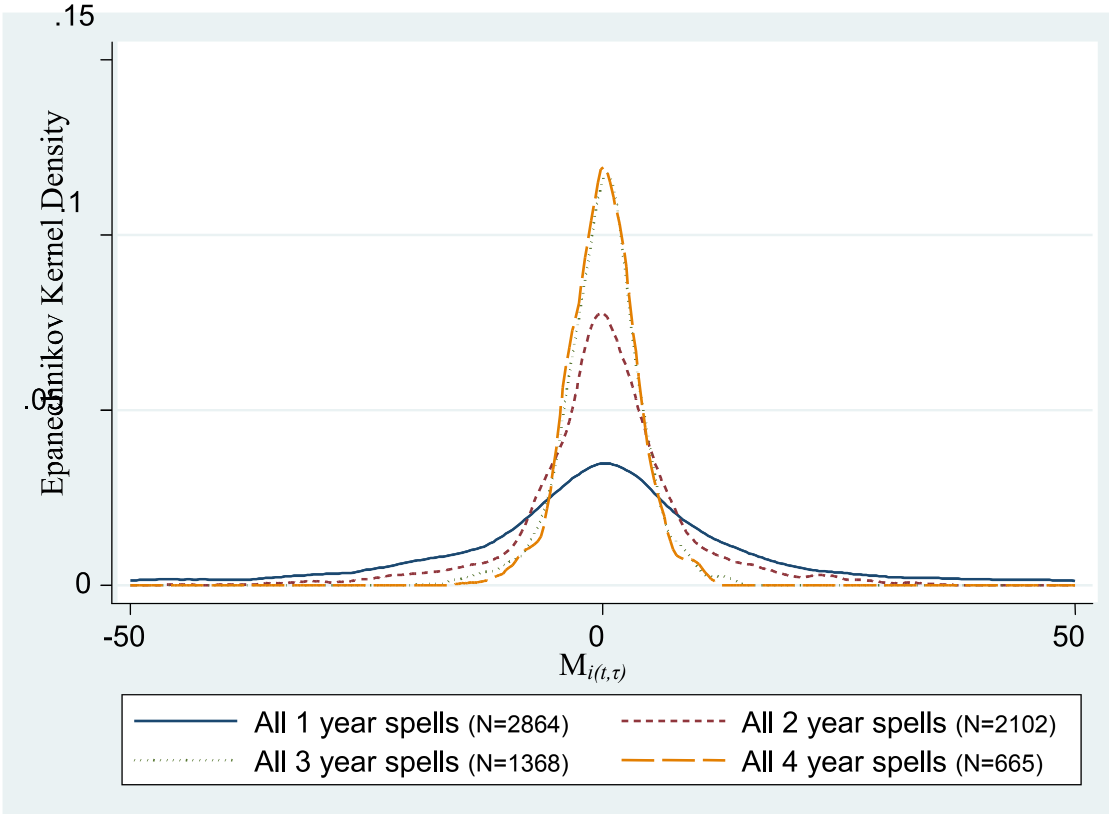

Figure 6 Kernel Densities of $M_{i(t,\tau)}$ for different income spell lengths

Statistical analysis confirms these results. Table 4 shows that the variance falls monotonically as the spell length increases from 1741 for the one year spells to 85, 17, 13 for the two, three and four year spells, respectively. Similarly, the kurtosis gets smaller as spells get longer, increasing the 'peakedness' of the distribution.

All kernel densities are highly non-normal as indicated by p-values of Anderson-Darling and Shapiro-Wilk test statistics that are very close to zero. However, the p-values for the Wilxocon-Mann-Whitney test between all spell lengths are high enough not to reject the hypothesis of equal medians for any two distributions. Hence, we can use the Ansari-Bradley and Fligner-Killeen tests to check for differences in variances. Their p-values very close to zero suggests that we can strongly reject the null hypothesis that any two empirical distributions of $M_{i(t,\tau)}$ have the same variance.[21] We can conclude that in rural Pakistan variability in incomes and, hence, apparent transitory poverty and total economic mobility, appears higher the shorter the interval between panel observations.

Table 4 Moments of Mi(t,τ) for different income spell lengths

	1 year spells	**2 year spells**	**3 year spells**	**4 year spells**
# obs.	2864	2102	1368	665
Mean	-0.23	0.11	-0.01	0.04
Median	0.19	0.10	0.21	0.06
Variance	1741.84	84.76	17.47	13.37
Kurtosis	17.12	10.66	4.64	3.80

How robust are these results to changes in the error autocorrelation structure? We address this question through Monte Carlo simulation. The structure of the simulated data is modeled on the PRHS data with five periods covering 700 households. Let y_{it} and y_{it}^* denote household *i*'s observed income and non-stochastic income, respectively. Further, let ε_{it} be a multiplicative error so that $y_{it} = y_{it}^* \varepsilon_{it}$. First period non-stochastic household income y_{i1}^* is drawn from a lognormal distribution with a range and variance calibrated on the PRHS data. The sampling distribution for the first

[21] An appendix of statistical test results is available by request.

period multiplicative error ε_{i1} is based on the actual errors from a second-order polynomial regression (with a full set of interaction terms) of income on assets using the PRHS data. Let e_{it} be this regression error.[22] Then $\varepsilon_{it} = \left(\frac{e_{it}}{y_{it}} + 1 \right)$ with $\varepsilon_{it} \in [0, \infty)$ and $E[\varepsilon_{it}] = 1$. For t>1, y^*_{it} is based on y^*_{it-1} plus three percent growth. For t >1 error terms ε_{it} were created using the same method as for ε_{i1}, but for three different autocorrelation structures. Let $\varepsilon_{it} = \rho\varepsilon_{it-1}$. Then the three cases ρ=1, ρ=0.5 and ρ=0 represent perfect and moderate positive autocorrelation and iid errors, respectively. For each of the three cases, we constructed stochastic incomes for all households for five time periods. The normalized average annual percentage change in log incomes per capita, $M_{i(t,\tau)}$, and the variance of $M_{i(t,\tau)}$ was then calculated for all spell lengths following equations 6 and 7. Each simulation was replicated 1000 times yielding the twelve distributions of variances summarized in Table 5 and Figure 7.

As expected, the mean variance of $M_{i(t,\tau)}$ varies depending on the autocorrelation structure. For a given spell length, the more errors are autocorrelated, that is, the greater ρ, the smaller the overall mean variance of annualized average percentage changes in per capita log income. This confirms our hypothesis $\overline{Var}\left(M_{i(t,\tau)}, \rho = 0\right) > \overline{Var}\left(M_{i(t,\tau)}, \rho > 0\right)$. It also makes intuitive sense as when ρ=0 then observed income $y_{it} = y^*_{it}\varepsilon_{it}$ has the largest variation over time. This is turn means that individual mobility $m_{i(t,\tau)}$ is most dispersed, hence, $Var\left(M_{i(t,\tau)}\right)$ is largest. The other extreme is shown in the last column in Table 5. When ρ=1 then transitory income is no longer stochastic, $M_{i(t,\tau)}$ and, therefore, $Var\left(M_{i(t,\tau)}\right)$, is effectively zero for any τ.

[22] For $e_{it} < 0$ we assume $\left|e_{it}\right| \leq y_{it}$, i.e., we preclude negative values for y_{it}.

Table 5 Mean variances of Mi(t,τ) for different autocorrelation structures based on 1000 replications

	Error Correlation Structure		
	Independent shocks ρ=0	Some persistence of shocks ρ=0.5	Cumulative advantage/ poverty trap ρ=1
Mean Variance ($M_{i(t,1\ year\ spells)}$) $\overline{Var}\left(M_{i(t,\tau(\min)=1}\right)$	299,144 [2,906,319]	2527 [77,100]	3.14-10 [6.52e-11]
Mean Variance ($M_{i(t,2\ year\ spells)}$) $\overline{Var}\left(M_{i(t,\tau=T-3}\right)$	226,418 [5,625,523]	24.06 [7.53]	6.84e-11 [2.21e-11]
Mean Variance ($M_{i(t,3\ year\ spells)}$) $\overline{Var}\left(M_{i(t,\tau=T-2}\right)$	791.81 [8889.54]	13.13 [3.07]	1.21e-11 [8.37e-12]
Mean Variance ($M_{i(t,4\ year\ spells)}$) $\overline{Var}\left(M_{i(t,\tau(\max)=T-1}\right)$	103.68 [530.07]	8.98 [1.73]	9.51e-12 [3.14e-13]

Notes: Standard deviations in brackets.

Table 5 and Figure 7 also show that the mean variance and its standard deviation fall monotonically as the spell length τ increases, mirroring the results from the PRHS data above.[23]

[23] The corresponding figure for ρ=0 is substantively the same as figure 2.

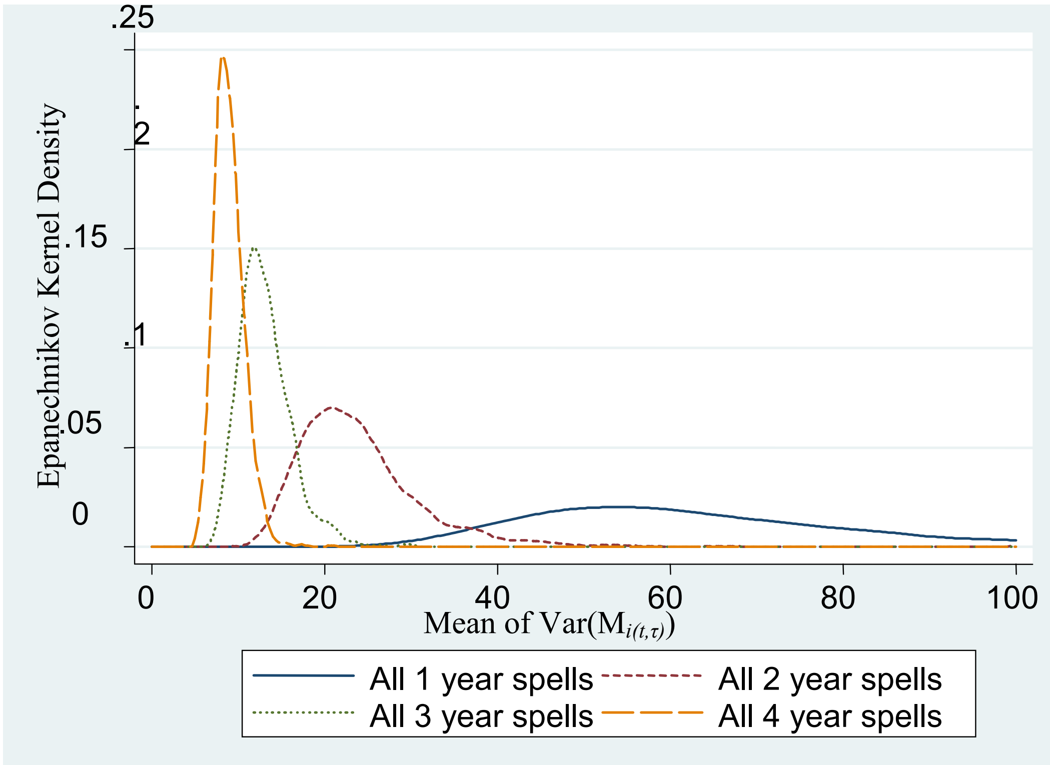

Figure 7 Kernel densities of mean variances of $M_{i(t,\tau)}$ from simulations (ρ=0.5)

4 Conclusions and Implications

The recent empirical literature on household income dynamics in developing countries has tended to conclude that a large proportion of poverty is transitory, and that relatively few households are chronically poor. In this note we propose and apply a test to detect whether such findings are at least partly driven by the length of time between panel observations.

Our application of the test to data from rural Pakistan as well as to simulated data shows that using short spells from high frequency panels likely overestimates structural economic mobility and, therefore, the degree of transitory poverty. Measures of total economic mobility capture non-stochastic economic mobility better when observed income spells are longer. An obvious corollary is that total economic mobility estimates based on short panel data spells need to be interpreted with caution as the ratio of stochastic to structural income changes is high. The variability in total incomes found in short spells can contain useful information for the design of income stabilization policies. However, our results indicate that estimates of total economic mobility based on short-term panel data are significantly greater than underlying structural income mobility that is the primary target of longer-term poverty reduction policies. Because of the truly stochastic component of transitory income this difference remains even when controlling for classical repeated measurement error and can only be reduced by collecting longer-running panel data.

APPENDIX

Controlling for measurement error in income

We can minimize the influence of measurement error on our economic mobility results following the approach of McCulloch and Baulch (2000). Let y_{it}^{*} and ε_{it}^{M} denote true unobservable household income and measurement error, respectively. Then observed income is

$$y_{it} = y_{it}^{*} + \varepsilon_{it}^{M} . \tag{A1}$$

If we make the classic errors-in-variables assumption then measurement error is uncorrelated with true income. Hence,
$Cov\left(y_{it}, \varepsilon_{it}^{M}\right) = E\left(y_{it}\varepsilon_{it}^{M}\right) = E\left(y_{it}^{*}\varepsilon_{it}^{M}\right) + E\left(\left(\varepsilon_{it}^{M}\right)^{2}\right) = 0 + \sigma_{\varepsilon^{M}}^{2}$.
If current income is a function of past true income and a stochastic error that is uncorrelated with past income,

$$y_{it}^{*} = \rho y_{it-1}^{*} + v_{it} \tag{A2}$$

but we use observed income y_{it} instead of true income y_{it}^{*}, then we actually estimate

$$y_{it} = \rho y_{it-1} + v_{it} - \rho\varepsilon_{it}^{M} \tag{A3}$$

Since the covariance of observed income and the composite error term is $Cov\left(y_{it}, v_{it} - \rho\varepsilon_{it}^{M}\right) = -\rho Cov\left(y_{it}, \varepsilon_{it}^{M}\right) = -\rho\sigma_{\varepsilon^{M}}^{2}$ the OLS estimate of ρ from equation A3 is not consistent. Its probability limit is

$$p\lim\left(\hat{\rho}_{OLS}\right)=\rho+\frac{Cov\left(y_{it},v_{it}-\rho\varepsilon_{it}^{M}\right)}{Var\left(y_{it}\right)}=\rho\left(1-\frac{\sigma_{\varepsilon^M}^2}{\sigma_y^2}\right) \tag{A4}$$

where the last term is the bias. Since we have panel data we can use lagged income to instrument for income. The resulting instrumental variable estimator of equation A3 is unbiased as $p\lim\left(\hat{\rho}_{IV}\right)=\rho$. Combining this with A3 we can estimate the ratio of noise variance to total observed variance (that is, the errors-in-variables bias) as

$$\frac{\hat{\rho}_{IV}-\hat{\rho}_{OLS}}{\hat{\rho}_{IV}}=\frac{\sigma_{\varepsilon^M}^2}{\sigma_y^2}=\frac{\sigma_y^2-\sigma_{y*}^2}{\sigma_y^2}=1-\frac{\sigma_{y*}^2}{\sigma_y^2} \tag{A5}$$

A5 is also equal to one minus the ‘reliability ratio’. The reliability ratio is a metric commonly used for expressing income measurement error in validation studies of economic mobility. Its estimates range from 0.67 to 0.87 (Abowd and Stinson 2005) encompassing our estimate of 0.75.

Since the actual measurement error is of course unknown we cannot reverse it. However, we can use the estimated ratio in A5 to construct measurement-error-adjusted household incomes as follows. Let $\bar{y}_i$ denote household *i*’s average observed income over time. Then adjusted household income is

$$\psi_{it}=\bar{y}_i+\left(y_{it}-\bar{y}_i\right)\frac{\sigma_{y*}}{\sigma_y} \tag{A6}$$

Since we assumed that measurement error has mean zero, adjusted income ψ has the same mean as observed income y: Rs3866. However, its standard deviation of 4157 is equal to the estimated variance of true unobserved income, which is smaller than the standard deviation of observed income of 4377. The deviations from mean household income are, therefore, scaled by the ratio of the standard deviations of true and observed income. Finally, note that since we cannot control perfectly for measurement error, estimating economic mobility using adjusted income gives an upper bound of true economic mobility.

Results

The IV estimation of equation A3 uses y_{it-2} as an instrument for y_{it-1}. Hence, y_{it-2} has to satisfy two assumptions. First, y_{it-2} is not correlated with υ_{it}. Second, y_{it-1} and y_{it-2} need to be reasonable well correlated, which they are with a correlation coefficient of 0.56.

Dependent variable: Real HH income per adult equivalent (y_{it})

Variable	*OLS*	*IV*
Real HH income per AE, 1st lag (y_{it-1})	.76467241***	1.0293571***
N	2867	2099
R-squared	.56509309	.
Instrument		y_{it-2}

Note: *** indicates significance at the 1% level.

Bias: $$\frac{\hat{\rho}_{IV}-\hat{\rho}_{OLS}}{\hat{\rho}_{IV}}=\frac{\hat{\sigma}^2_{\varepsilon^M}}{\hat{\sigma}^2_y}=0.2581$$

Reliability Ratio: $r=1-bias=1-0.2581=0.7419$

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Chapter 4:
Measuring Poverty Over Time -
Accounting for welfare variability and the intertemporal distribution of poverty

1 Introduction

Poverty measures tend to be static. Poverty rates calculated from single surveys give snapshot views of poverty. Even the assessment of poverty over time generally does not go beyond looking at poverty trends, that is, comparing snapshot cross-sectional poverty indices at two or more points in time. While analytically simple, snapshot poverty measures are unlikely to fully characterize poverty over time at the level of the individual household and at the aggregate level of society.

At the individual household level, snapshot poverty measures are independent of a household's income and poverty status in previous and subsequent periods. But of course these household income and poverty 'histories' can influence how one perceives and thinks about poverty. For example, for a given amount of total income[24] over time, income mobility in the form of fluctuations in incomes reduces welfare under the standard assumption of concave utility. For a given variance, upward trends in income are likely to be preferred to random fluctuations, which in turn are preferable to downward trends. Welfare would be lower the greater the uncertainty of future incomes. Similarly, standard snapshot poverties fail to capture society-wide effects of fluctuations in income. Imagine one society with no income mobility in which half the population is in chronic poverty and the other half is never poor. Now

[24] In this paper I use the term 'income' as a short-hand for material well-being. However, the discussion applies equally to any other uni- or multi-dimensional indicator of well-being.

picture another society with the same amount of aggregate income over time, but in which there is no chronic poverty, but lots of (zero-sum) mobility so that everyone spends some time in poverty. Would we judge them to be equally poor? If we believe that any of these household and society-level fluctuations in income and poverty status affect social welfare then our poverty measures should attempt to reflect this.

One main objective of this paper is, therefore, to develop new classes of poverty measures which are sensitive to households' income variability and to the degree to which poverty is shared across households over time. A second objective is to compare these new measures with the few other existing measures proposed in the literature to date which have attempted to account for intertemporal variation in households' welfare. These comparisons will highlight that the choice of how to account for income variability and the intertemporal distribution of poverty will depend on the particular policy or evaluation objective. For example, if the objective is to minimize the proportion of the population that experiences poverty over time we would use a different poverty measure to measure against than if the objective is to reduce the total poverty cost from income variability. The third objective is to apply the new and existing poverty measures to survey data from rural Pakistan to demonstrate the extent to which different methods to account for income variability and the intertemporal distribution of poverty affect estimated poverty measures.

The next two section introduces some analytic preliminaries. Section 3 discusses two methods for making poverty measures sensitive to income variability and applies these to panel data from rural Pakistan. Section 4 outlines three ways of accounting for the intertemporal distribution of poverty across households and applies them to the same dataset. Section 5 concludes.

2 Measuring poverty over time: Some preliminaries

Measuring household poverty over time requires either longitudinal or pseudo-panel data. A (pseudo-)panel contains a sequence of income observations for each household (type) $i \in \{1, 2, ..., N\}$ at each time period $t \in \{1, 2, ..., T\}$. Let x_{it} and y_{it} denote i's income at t for two societies' intertemporal income profiles which we wish to compare. The panel information can be represented by society income matrices A and B in 1.

$$A = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1T} \\ x_{21} & x_{22} & & x_{2T} \\ \vdots & & & \vdots \\ x_{N1} & x_{N2} & \cdots & x_{NT} \end{bmatrix} \quad B = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1T} \\ y_{21} & y_{22} & & y_{2T} \\ \vdots & & & \vdots \\ y_{N1} & y_{N2} & \cdots & y_{NT} \end{bmatrix} \tag{1}$$

In an ex post analysis the elements of A and B are known past incomes. We can then choose a sequence of poverty lines $Z = \{z_1, .., z_T\}$ [25] to accompany the panel matrices, and calculate poverty levels for each element in A and B as in P(A) and P(B).

$$\begin{aligned} P(A) &= \begin{bmatrix} p(x_{11}, z_1) & p(x_{12}, z_2) & \cdots & p(x_{1T}, z_T) \\ p(x_{21}, z_1) & p(x_{22}, z_2) & \cdots & p(x_{2T}, z_T) \\ \vdots & \vdots & \ddots & \vdots \\ p(x_{N1}, z_1) & p(x_{N2}, z_2) & \cdots & p(x_{NT}, z_T) \end{bmatrix} \\ P(B) &= \begin{bmatrix} p(y_{11}, z_1) & p(y_{12}, z_2) & \cdots & p(y_{1T}, z_T) \\ p(y_{21}, z_1) & p(y_{22}, z_2) & \cdots & p(y_{2T}, z_T) \\ \vdots & \vdots & \ddots & \vdots \\ p(y_{N1}, z_1) & p(y_{N2}, z_2) & \cdots & p(y_{NT}, z_T) \end{bmatrix} \end{aligned} \tag{2}$$

[25] Alternatively, incomes and poverty lines could be normalized so that we only need to use one z for all periods.

Assume that household[26] poverty over time is a function of the stream of incomes received over time and the variability of income. Lifetime poverty for household *i* is then a row aggregation of the society income matrix and can be defined as: $LP_i = V\left(x_{i1},...,x_{iT};z_1,...,z_T\right)$, where T=(1,…T) is time, $\left(x_{i1},...,x_{iT}\right)$ is household *i*'s income history, $\left(z_1,...,z_T\right)$ is the sequence of poverty lines and $V:\mathbb{R}^t \rightarrow \mathbb{R}$ is the valuation function which maps the sequence of incomes and poverty lines into the real line.

Income variability describes ex post income fluctuations and is, thus, a backward looking concept. As such, it is a tool for analyzing past performance, just like any commonly used measure of well-being. Note, however, that examining past variability can also be useful for planning future policies in the following way. If we are willing to assume that the distribution of a household's past incomes is a probability distribution and that this probability distribution is stationary over time, then we can think of the observed ex post income variability as also representing the household's ex ante risk and vulnerability.[27] Indeed, much of the recent literature on vulnerability measurement is based on these assumptions (Pritchett *et al.* 2000; Ligon and Schechter 2003). For now, however, this paper focuses on the effects of ex post income variability on well-being.

Now consider the economy-wide level. At each point in time a society suffers from a certain level of poverty. Over several points in time this burden can be summed up into the aggregate intertemporal poverty burden. Define the intertemporal distribution

[26] Throughout the paper I refer the 'household' as that is the level for which we generally have income survey data. However, we can think of it as the 'individual' for variables for which we have person-specific data, such as education, health or nutrition.

[27] The stationarity assumption also implies that there is no change over time in the risks a household faces, and no change in ex ante risk coping strategies (e.g., choosing low risk low return investments).

of poverty to be the way this aggregate intertemporal suffering from poverty is shared across households. Total lifetime poverty for a society can be expressed as: $TLP = P_{AGG}(LP_1, ..., LP_q)$, where q is the number of households who are poor in at least one period. The aggregation function P_{AGG} needs to aggregate across household lifetime poverties as well as take account of the intertemporal distribution of poverty across households.

A poverty measure that is sensitive to the intertemporal distribution of poverty thus captures the – normative, but reasonable – claim that the extent of aggregate intertemporal poverty in a society depends not only on the aggregation of 'snapshot' single period cross-sectional poverty indices, but also on the distribution of poverty durations across households. Specifically, sharing poverty more equally across society is assumed to reduce the burden of intertemporal aggregate poverty.

This assumption is reasonable in a variety of circumstances. First, if our evaluation of social welfare depends on 'fairness' in the sense that some of the differences in poverty durations across households are structural and not a result of differing levels of effort or risk taking. Second, if we believe that each individual household's poverty experience gets worse with increasing length of poverty. For instance, at the household level chronic poverty can have a permanent effect on health, employability, and psychological well-being. Third, if there are neighborhood effects in the sense that the poverty experience of one household affects the well-being of other households. Fourth, if there are economy-wide negative consequences from chronic poverty. For example, overall investment and output may be depressed due to social tensions and civil unrest, and due to some members of society being permanently excluded from higher return activities.

The same concept - variability in household incomes – has two opposite effects depending on how we choose to measure income and poverty. For individual households it reduces welfare compared to a constant income stream, but at the aggregate level greater income mobility, in the form of churning, is a positive. Neither of these two opposite effects is right or wrong, but it does suggest that we need to pick income and poverty measures according to the particular issue we are interested in. Indeed, both the household and the aggregate methods of accounting for income variability can be a valuable addition to poverty analysis as they both capture aspects of poverty that standard poverty measures (implicitly) ignore.

3 Lifetime household poverty & income variability

This paper's motivation for incorporating income variability into a measure of household poverty is depicted in Figure 8. The household income histories in case 1a and 1b have the same average income below the poverty line z, but does the income variability in 1b make it poorer than 1a? Similarly, 2a and 2b have the same average income, this time above z. Is 2b poorer than 2a? The answer is 'yes' in a wide variety of circumstances.

For example, if we believe any of the following are true: households are averse to income fluctuations; household incomes are not truly separable over time, for instance, due to imperfect access to financial markets; there are no irreversibilities so that households can physically and materially recover from periods in poverty; and there are no stigma costs to having experienced poverty.

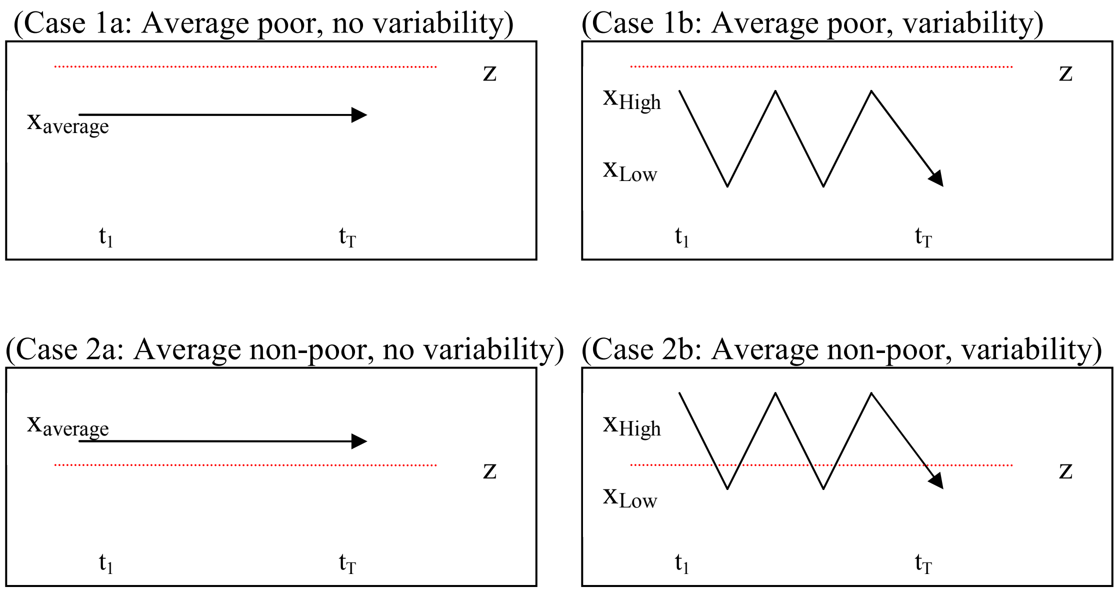

Figure 8 Stylized household income histories – with and without income variability

This section introduces two classes of poverty and income measures to account for intertemporal variability in household income. They offer two distinct ways of summarizing the income history of each household *i*, $\left(x_{i1},...,x_{iT}\right)$ into a single lifetime household income number.

In deriving these intertemporal poverty measures it is useful to define a household 'illfare from poverty' function based on the Foster-Greer-Thorbecke (1984) index (FGT)[28]

$$W(x_{it}) = \begin{cases} -\left(\dfrac{z_t - x_{it}}{z_t}\right)^{\alpha} & if\ x_{it} < z_t \\ 0 & if\ x_{it} \geq z_t \end{cases} \tag{3}$$

[28] The choice of this particular form is motivated in the next section.

where α is household i's intertemporal poverty aversion parameter. This function satisfies the focus axiom of static poverty measures in the sense that a household which is never poor has zero lifetime illfare from poverty.

Two approaches for making intertemporal household poverty measures sensitive to income variability

A measure of intertemporal household welfare can be made sensitive to income variability in two ways. The first can be termed the *constant equivalent income* approach to measuring intertemporal household poverty. Let δ be the discount factor and $z = \frac{1}{T}\sum_{t=1}^{T}\delta^t z_t$ be the intertemporal poverty line. Then the constant stream of i's income that results in the equivalent poverty as the actual household lifetime poverty $LP_i(\alpha)$ is defined as:

$$CEIP_i \equiv \frac{1}{T}\sum_{t:x_{it}<z_t}\delta^t\left(\frac{z_t - x_{it}}{z_t}\right)^{\alpha} \equiv \left(\frac{z-\overline{x}_i}{z}\right)^{\alpha} \tag{4}$$

For each i we can find a constant equivalent income (*CEI*) $\overline{x}_i$ which gives the same illfare from poverty as i's actual income stream. $\overline{x}_i$ depends inversely on α. For a given income history, as i's aversion to income variability increases its *CEI* falls. The constant equivalent income poverty (*CEIP*) definition in equation 4 distributes any poverty i experiences equally across all t. Hence, in addition to aversion against variability the *CEIP* implies strong poverty aversion. Periods where i is non-poor cannot compensate for periods spent in poverty. This is a result of the shape of the social 'illfare' function W(.) above, which gives the value of zero to all observations above z. For example, if all but one x_{it} are well above their z_t's, but one is below, then $\overline{x}_i$ is still less than z_t. The *CEI* can be plugged into a regular FGT poverty measure to yield a simple measure of the total average lifetime poverty for society: $TLP = \frac{1}{N}\sum_{i:\bar{x}_i<z}\left(\frac{z-\bar{x}_i}{z}\right)^{\alpha}$. Using equation 4 to replace $\bar{x}_i$ with x_{it} and rearranging gives

$$TLP = \frac{1}{N}\sum_{i:\bar{x}_i<z}\left(\frac{1}{T}\sum_{t:x_{it}<z_t}\delta^t\left(\frac{z_t-x_{it}}{z_t}\right)^{\alpha}\right) = \frac{1}{NT}\sum_{i:\bar{x}_i<z}\sum_{t:x_{it}<z_t}\delta^t\left(\frac{z_t-x_{it}}{z_t}\right)^{\alpha} \tag{5}$$

Note that this is not equivalent to the simple case of aggregating matrix A horizontally (over *t*) and then vertically (over *i*). That would count the ever-poor households only in periods where they below *z*. In contrast, the second summation in equation 5 sums across all households whose constant income $\bar{x}_i$ is below *z*.

In terms of implementing the constant equivalent income approach to measuring intertemporal household poverty it is worth noting that it gives unsatisfactory results for the headcount ratio. To illustrate rewrite equation 4

$$CEIP_i(\alpha) = \frac{1}{T}\sum_{t:x_{it}<z_t}\left(\frac{z_t-x_{it}}{z_t}\right)^{\alpha} = \begin{cases}\left(\frac{z-\bar{x}_i}{z}\right)^{\alpha} & if\ \bar{x}_i < z \Leftrightarrow \exists x_{it} < z_t \\ 0 & if\ \bar{x}_i \geq z \Leftrightarrow x_{it} \geq z_t \forall t \in T\end{cases} \tag{6}$$

Then in the case of α=0, if household *i* has ever experienced poverty its $CEIP_i(0)$ is equal to one and its constant equivalent income $\bar{x}_i(0)$ could be *any* income below *z*. Symmetrically, if *i* has never been poor then its $CEIP_i(0)$ is equal to one and any $\bar{x}_i(0)$ above *z* can be its constant equivalent income. This extreme result is due to the discontinuous nature of the headcount index.

The constant income approach is less extreme and, therefore, more appealing for α greater than 0. For α=1 and α=2, $\overline{x}_i$ can be calculated as follows.

$$CEIP_i(1) = \left(\frac{z - \overline{x}_i}{z} \right) \Rightarrow \overline{x}_i\left(\alpha = 1\right) = z\left[1 - CEIP_i(1)\right] \tag{7}$$

$$CEIP_i(2) = \left(\frac{z - \overline{x}_i}{z} \right)^2 \Rightarrow \overline{x}_i\left(\alpha = 2\right) = z\left[1 - \sqrt{CEIP_i(2)}\right] \tag{8}$$

From equations 10 and 11 we see that the $CEIP_i(1)$ and $CEIP_i(2)$ for never poor households are equal to zero. This means that the right hand sides of equations 10 and 11 are also equal to zero, forcing $\overline{x}_i\left(\alpha\right)$ to be equal to *z*. Therefore, calculating the constant equivalent incomes for non-poor households does not provide additional information for any poverty analysis. The never-poor households are therefore excluded from the calculation of constant equivalent income. This also ensures that the constant equivalent income approach is in line with Sen's (1976) focus axiom. For ever-poor households the constant equivalent income is a useful indicator of the cost of income variability if we believe that having ever experienced poverty is not - or at least not completely - reversible.

The second, alternative way of making social welfare sensitive to income variability can be called the *stability equivalent income* approach. This approach exploits the mathematical analogy between ex ante expected utility and income risk on the one hand and ex post utility and income variability on the other. In an ex ante world we are dealing with expected utility, which is based on the range of possible states of the world denoted by the outlined dots in Figure 9 to the right of the present time (*time*=0). Since we have uncertainty over the states of the world the contingent income for each state is a random variable. The expected income and, thus, utility depends not only on the incomes in each state but also on their distribution, i.e., the probability with which each income happens. Figure 9 depicts a world with two equally likely states, high income x_{High} and low income x_{Low}, and an expected income of E(x). If, as usual, we assume a concave utility function to represent risk aversion then the certainty equivalent income CertEI lies below E(x) by Jensen's inequality. The Arrow-Pratt coefficients of absolute and relative risk aversion are positive and the difference between CertEI and E(x) represents the risk premium.

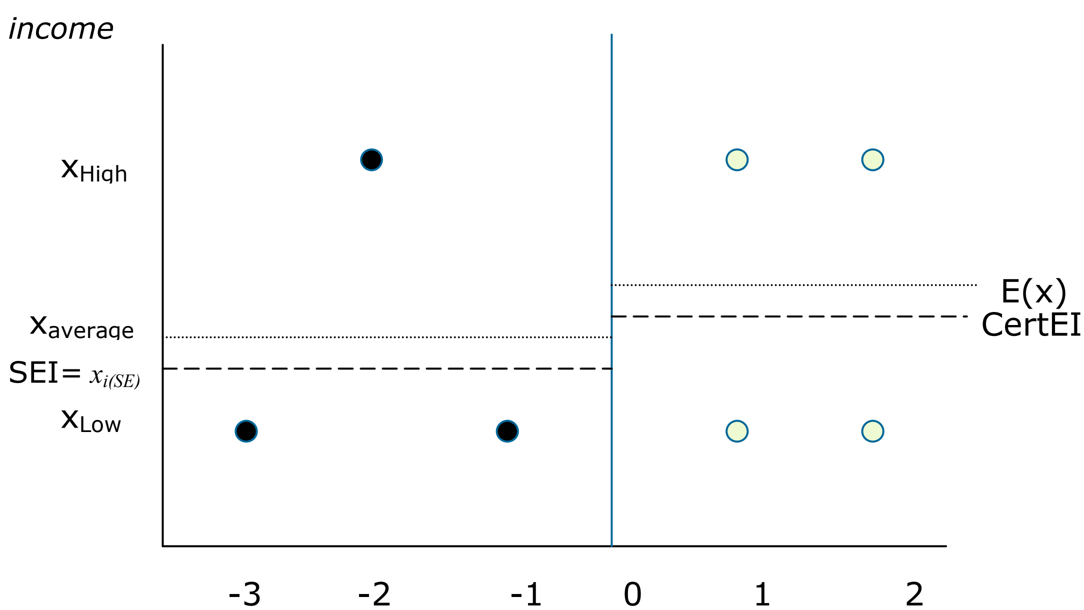

Figure 9 Analogy of ex ante income risk and ex post income variability

In an ex post world we observe a sequence of past incomes denoted by the black dots to the left of 'now'. While past incomes show some variation over time they are, of course, no longer random variables. However, the mathematics carry over from the stochastic ex ante world. States of the worlds are now replaced by actual realizations of past household incomes at *time*<0 and the utility function over certain past incomes replaces the expected utility over uncertain future states.

The examples in Figure 9 and Figure 10 show the case of income variability aversion where average income, $x_{average}$, lies above the stability equivalent income, $x_{i(SE)}$. When a household is variability averse the welfare function W(.) is concave, the coefficients of absolute and relative variability aversion are positive, and a household would be better off if it earned its average income in each period, as $W(x_{i(SE)})<W(x_{average})$. The absolute and the relative variability premia[29] V_A and V_R can be defined as:

$$V_A = x_{average} - x_{i(SE)} \tag{9}$$

$$V_R = \frac{\left(x_{average} - x_{i(SE)}\right)}{x_{average}} \tag{10}$$

For a given level of variability aversion, the absolute and relative variability premia therefore show the additional amount and percentage of income, respectively, needed to compensate for income variability to maintain the same amount of poverty. Interpreted differently, the stability equivalent premium indicates the upper limit of welfare gains from income stabilization; or, similarly the upper limit of the welfare loss (in currency or in Poverty Measure units) due to fluctuations in past incomes.

[29] As this paper has gone through revisions the concepts of stability equivalent incomes, variability premium, constant relative and absolute variability aversion welfare functions and coefficients of relative and absolute variability aversion have been proposed in another PhD thesis (Cruces 2005).

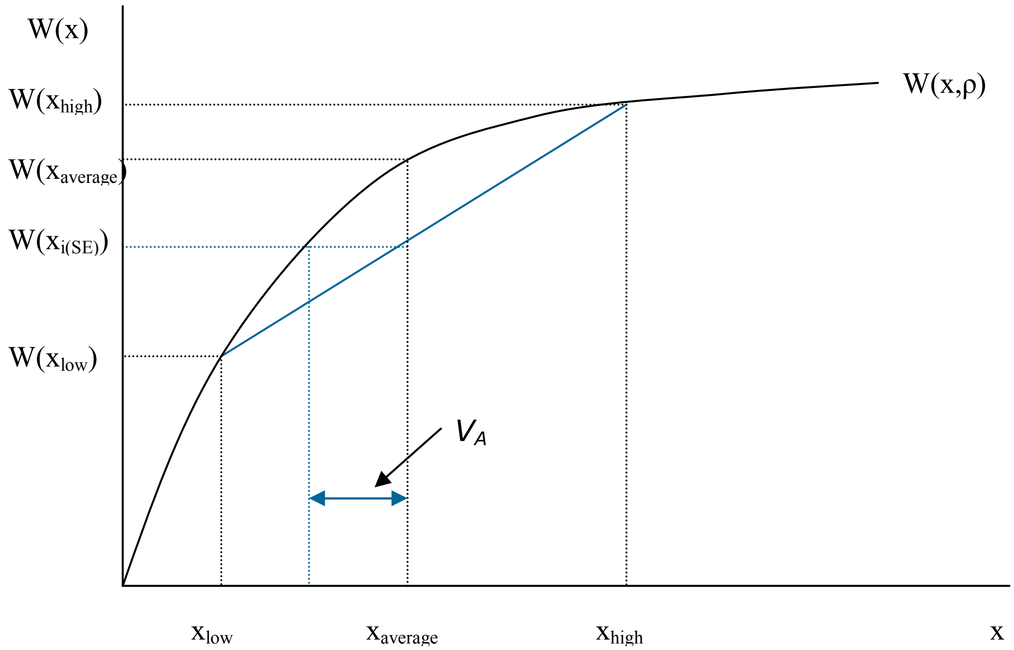

Figure 10 Stability Equivalent Income and Variability Premium under Variability Aversion

To implement the stability equivalent income approach we need to choose a functional form to penalize past income variability. Analogously to ex ante constant relative risk aversion we can define a household's lifetime SEI, $x_{i(SE)}$, using a constant relative variability aversion (CRVA) function:

$$x_{i(SE)} = \begin{cases} \left[\frac{1}{T} \sum_{t=1}^{T} \delta^t x_{it}{}^{1-\rho} \right]^{\frac{1}{1-\rho}} & if\ \rho \neq 1 \\ \prod_{t=1}^{T} \delta^t x_{it}{}^{1/T} & if\ \rho = 1 \end{cases} \tag{11}$$

where ρ is the constant relative variability aversion coefficient. Again, a matching poverty line can be written as $z = \frac{1}{T} \sum_{t=1}^{T} \delta^t z_t$.

By choosing different values of ρ we can allow for different households' preferences towards income fluctuations or, equivalently, tailor our lifetime household poverty measures to the social planner's preferences and the particular policy objective at hand. Increasing the value of ρ would be appropriate as the policy objective moves from maximizing aggregate income towards the 'safety first' goal of minimizing (downward) fluctuations. Figure 11 shows the two limiting cases of ρ =0 and $\rho \to \infty$ and the intermediate case where ρ is a finite positive number.

When there is no fluctuation in income so that x_{i1}=x_{i2}, or when ρ is equal to zero and households are 'variability neutral' we are at point $x_{i(SE,\rho=0)}$ in figure 11. The stability equivalent income evaluation function reverts back to the straight average of household intertemporal income:

$$x_{i(SE)}^{\rho=0} = \frac{1}{T}\sum_{t=1}^{T} \delta^t x_{it} \tag{12}$$

This gives us the upper limit of the lifetime household income range and represents the utilitarian version[30] of equation 14. Often this is reported in studies which do not explicit set out to account for income variability. Note that $x_{i(SE)}$ may be lower than the snapshot poverty in each t (Grootaert and Kanbur 1995). As the level of ρ increases the stability equivalent income penalizes income variability more and, hence, increases lifetime poverty compared to simply aggregating snapshot poverty levels.

[30] Utilitarian in the 'intertemporal within household' sense, where each household is only interested in maximizing the sum of its discounted income stream, not in the distribution of income over time.

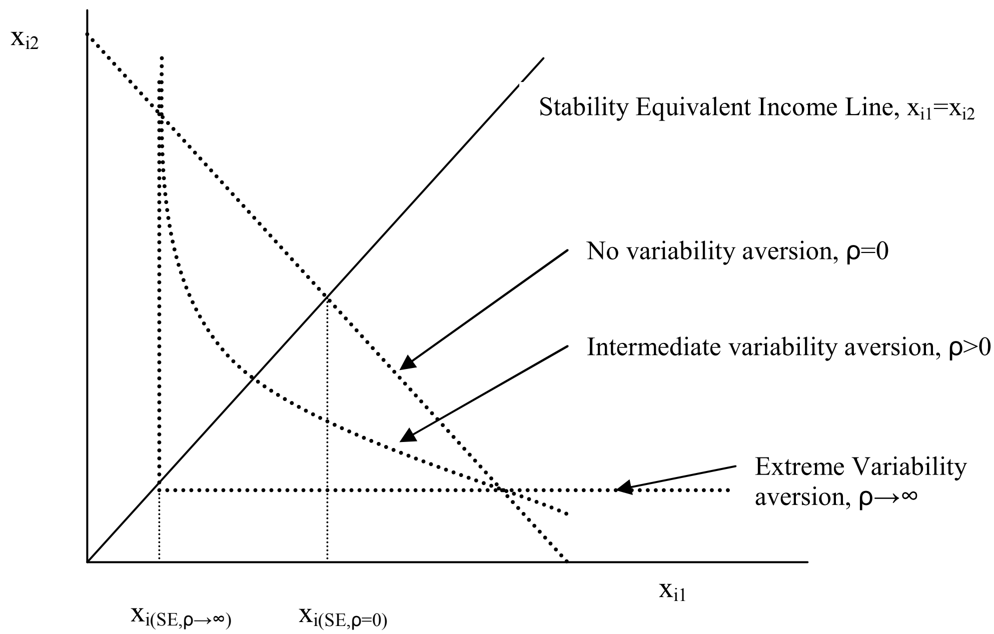

Figure 11 Stability Equivalent Income (2 periods, different values of ρ)

The lower limit is marked by the case when $\rho \to \infty$. This represents the Rawlsian version of equation 14 where households are averse to any degree of income variability, indicated by the point $x_{i(SE,\rho\to\infty)}$ in figure 1. In this case the stability equivalent income reduces to the lowest single period income for a household:

$$x_{i(SE)}^{\rho\to\infty} = \min(x_{it}) \tag{13}$$

On the basis of these SEI's we can then calculate total variability adjusted lifetime poverty in society. First construct the N-vector $x_{(SE)} = \left(x_{1(SE)}, x_{2(SE)}, ..., x_{N(SE)}\right)$ such that the $x_{i(SE)}$'s are ordered from lowest to highest. Then applying the FGT yields the stability equivalent income poverty aggregate:

$$SEIP(\mathbf{x}_{(SE)}, \alpha, \rho) = \frac{1}{N}\sum_{i=1}^{q}\left(\frac{Z - x_{i(SE)}}{Z}\right)^{\alpha} \tag{14}$$

Why and when should one choose the constant equivalent income method or the stability equivalent income method of adjusting lifetime household poverty for income variability? Neither method is better than the other per se. Instead, the choice of how to adjust incomes and poverty rates for variability depends on how the properties of each of the two methods suit the particular evaluation question at hand and/or on one's assumptions about how households' lifetime welfare are affected by spending any time in poverty.

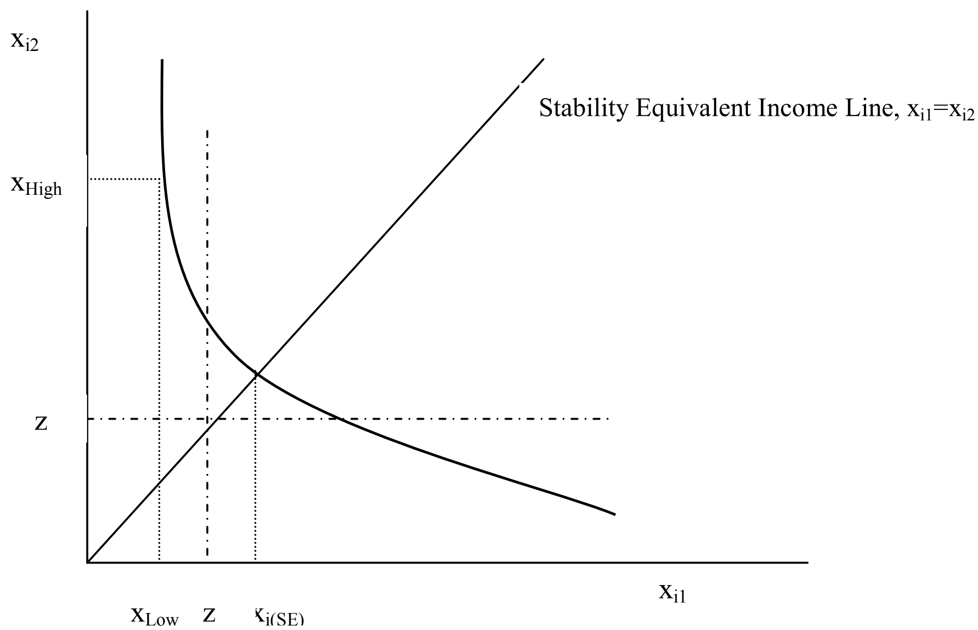

Figure 12 Different levels of poverty under CEI and SEI for the same lifetime household income

Both the stability equivalent and the constant equivalent income approach imply aversion to income variability, but only the latter implies poverty aversion. To see this consider the lifetime poverty of an 'ever-poor' household based on the stability equivalent approach in Figure 12. The income in period 1 is x_{Low}, which is below the poverty line z, while period 2 income x_{high} is above z. Then the household's lifetime poverty is zero as long as the stability equivalent lifetime income, $x_{i(SE)}$, is above z. Time spent in poverty can be made up by being 'sufficiently' non-poor in other periods. In contrast, under the constant equivalent income approach the household would be poor as $x_{Low} < z$ and a household cannot fully recover from having ever been poor.

Table 6 summarizes the conceptual and technical differences between the constant equivalent and the stability equivalent approach to measuring income and poverty that were discussed in this section.

Table 6 Differences between Constant Equivalent Income and Stability Equivalent Income

	Constant Equivalent Income Poverty, *CEIP*	Stability Equivalent Income Poverty, *SEIP*
Policy Objective	Minimize number of HHs ever in poverty ('thresholds')	Minimize cost of any income variability (↑ρ→ "safety first")
Preserves HH poverty histories $\left(x_{i1},\ldots,x_{iT}\right)$	Yes (remembers any $x_{it}<z_t$)	No (aggregated into the $LP_i(\alpha)$)
Poverty Aversion/ Irreversibility	Yes (by discontinuity in *W*)	No
Variability aversion	Only if poor in 1 to T-1 periods Trivial variability aversion due to α and δ.	Yes (due to ρ) Trivial variability aversion due to δ.

Table 6 (Continued)

Choice parameters Can express social welfare loss in income terms	δ,α(in income calculation) Yes (as difference between CEI and average income)	δ,α(in poverty calculation),ρ Yes (as variability premium)
Can express social welfare loss in poverty terms	No	Yes
Implies concavity of evaluation function	No	Yes
Continuous across z	No	Yes
Poverty index applied	NxT times (to each x_{it})	N times (to each $LP_i(\alpha)$)
Interpretation 1	For a given amount of poverty what is the loss of income from variability? What is the income loss you are willing to take if income was stabilized?	For a given amount of income what is the poverty increase and income loss from variability?
Interpretation 2	The richest poor 'lose' the most. ('threshold' motivation)	Everyone loses proportionately from variability.

The Data

To test empirically to what extent accounting for income variability and the intertemporal distribution of poverty makes a difference, the poverty measures discussed in this paper are applied to data from the Pakistan Rural Household Survey (PRHS). This survey was conducted by the International Food Policy Research Institute (IFPRI) and spans 14 rounds between July 1986 and October 1991. It contains data for around 900 rural households in 46 villages located in four districts in three provinces: Badin in Sindh, Dir in the North Western Frontier Province, and Attock and Faisalabad in Punjab. As often with rural panel surveys, the selection of districts was not random; the first three were selected specifically because they are among the poorest in their province. The richer district of Faisalabad was included as a contrast. The survey is therefore not representative for Pakistan as a whole. It should, however, reflect conditions in poor rural areas. Villages within districts and household within villages were selected by stratified random sampling. Due to the irregular spacing of rounds across the five years the data display varying degrees of seasonality. To overcome this I follow previous studies that have used these data, for example Baulch and McCulloch (1998), and combine rounds by year to construct annual data.

The data include 773 households for which we have income data for any of the five years. To illustrate the full effect of intertemporal income variability I only kept household for which we have income data for all five years (this throws out 97 households) and for which income is positive in all time periods (this eliminates another 9 households), yielding a balanced panel of 667 households.

Following previous studies that have used the IFPRI panel (Alderman and Garcia 1993; Adams and He 1995; McCulloch and Baulch 2000) I use a relative poverty line set to equal the 20th percentile of the distribution of adult equivalent income in 1986/87, the first year of the panel. This works out to be RS 2000 per adult equivalent and is also roughly equal to the level of expenditure needed to purchase 2100 calories per adult per day. Using this relative poverty line also circumvents the problem of not having a reference basket of goods for the survey villages that could be used to calculate the cost of basic needs.

Estimating the effect of variability on incomes and poverty

Some summary measures of income mobility are useful to get a sense of the magnitude of income variability in the sample from rural Pakistan. Symmetric income movements per household as measured by the Fields-Ok (1996) measure[31] range between Rs380 and Rs408 for the five years covered by the survey. These movements represent between 9.7 and 11.3% of average incomes. Expressed in terms of relative movements in the income distribution, the variations in household incomes mean that on average households moved approximately one income quintile from each year to the next. In short, there is a lot of income movement among households in rural Pakistan which makes this dataset suitable for exploring the effect of income variability on lifetime household poverty and income.

The analysis below reports results for whole sample of the PRHS and individually for each district. The prime reason to include the districts separately is because the poverty and income measures proposed in this paper are novel and, therefore, lack benchmarks. Thus, only a comparative analysis enables one to gauge whether, and in what way, the proposed extensions yields different poverty rates than standard poverty measures. Comparing districts also shows whether different methods of accounting for income variability leads to different poverty rankings.

To put the effects of income variability on income and poverty measures into perspective, consider two poverty baselines as reference points. Baseline A represents poverty rates in the pooled cross section. By treating the panel data as NxT 'cross-sectional' observations it loses the household specific income histories $\left(x_{i1},...,x_{iT}\right)$. This has two consequences: First, it is immaterial whether the cross-sectional aggregate poverty is made up of some households that are chronically poor, or if it

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[31] $m^{(1)}{}_N\left(x_t, y_t\right) = \frac{1}{N}\sum_{i=1}^{N}\left|x_{i,t} - x_{i,t-1}\right|$

results from all households being poor some of the time. Second, any time spent in poverty by any household cannot be compensated.

Baseline B represents the extreme case of no variability aversion. It is related to Ravallion's (1988) measure of chronic poverty as it treats households as poor only if their average (or expected) income is below z. Thus, Baseline B does not register any negative welfare cost from income variability. The effects of variability are eliminated by first summing incomes for each household over time so that incomes below the poverty line are compensated Rupee for Rupee by other periods' incomes above z. This total intertemporal household income combined with the total period poverty line (i.e., $\sum_{t=1}^{5} \delta^t z_t$ since we have five years of income data) gives us the Baseline B poverty indices. When households are neutral towards variability in income so that ρ=0, then stability equivalent income poverty *SEIP* is identical to baseline B. This baseline is, therefore, the lower limit for poverty rates under the stability equivalent income approach. As variability aversion ρ rises *SEIP* goes up.

Table 7 shows that, as expected, baseline B is substantially lower than Baseline A for the whole sample as well as for the individual districts. For example, the headcount for all districts is eight percentage points lower. This gives an indication of the effect on poverty rates of using average incomes and thus ignoring variability of incomes. Much as the baselines differ, neither is 'wrong'. However, the magnitude of the difference means that it is important to be clear about why we want to use one baseline over another. The choice of baseline and of the method for accounting for income variability should depend on the aspect of poverty (and the policy evaluation question) we are interested in.

Table 7 Baseline Poverty Measures

		FGT index		
		α=0	α=1	α=2
Baseline A				
Pooled Cross Section	All districts	0.296	0.096	0.046
	Faisalabad	0.234	0.061	0.025
	Attock	0.413	0.151	0.081
	Badin	0.305	0.091	0.041
	Dir	0.264	0.086	0.040
Baseline B				
Average long single HH poverties	All districts	0.214	0.044	0.014
	Faisalabad	0.152	0.021	0.004
	Attock	0.365	0.098	0.038
	Badin	0.219	0.048	0.016
	Dir	0.167	0.027	0.006

Next let us examine how accounting for income variability affects these baselines. Under the constant income approach we need to find the level of constant income that would result in the same amount of poverty as the average of the individual period household poverties. From equation 4 we see that by definition the total poverty over time under the constant equivalent income approach is the same as the average poverty actually experienced. One way to look at the welfare cost of variability is to examine the differences between the average actual income and the corresponding constant equivalent income $\overline{x}_i$ from equation 4.

In these data, 421 households have an *LPi(α)*>0. This defines the sample for the constant equivalent income approach as it means that these households were poor in at least one period. The average mean income of these ever-poor households in all districts is Rs2606. This is much higher than the mean constant equivalent incomes from equations 4 and 5 reported in the first column in table 8. $\overline{x}_i$ based on α=1 and α=2 are only Rs1704 and Rs1553, respectively. This means that the effect of income variability for the average household is equivalent to losing between 902 and 1053

Rupees (or 27 and 34% of household income) based on the poverty gap and the squared poverty gap. Since the estimated percentage shortfalls from average income in table 8 compare actual variable household incomes with stabilized mean incomes, they can be viewed as an upper bound of welfare improvements that would have been possible had past incomes been stable at their mean. The percentage shortfall from average income rises as the Constant Equivalent Income measures get more distributionally sensitive. This is to be expected as income variability causes more lower income draws, and as higher values of α put more weight onto lower incomes.

Table 8 Constant Equivalent Incomes and Percentage Shortfalls from Average Incomes

	# of obs	Mean	Percentile				
			10%	**25%**	**50%**	**75%**	**90%**
All Districts	**421**						
Average Intertemporal Income		**2606**	**1462**	**1838**	**2393**	**3069**	**4078**
Constant Equivalent Income, $\overline{x}_i(\alpha=1)$		1704	1364	1573	1775	1905	1959
% Shortfall from average income, α=1		27%	2%	11%	25%	40%	54%
Constant Equivalent Income, $\overline{x}_i(\alpha=2)$		1553	1144	1344	1590	1801	1912
% Shortfall from average income, α=2		34%	11%	20%	32%	45%	59%
Faisalabad District	**82**						
Average Intertemporal Income		**2772**	**1688**	**2061**	**2656**	**3334**	**4175**
Constant Equivalent Income, $\overline{x}_i(\alpha=1)$		1791	1474	1675	1844	1951	1979
% Shortfall from average income, α=1		28%	8%	18%	30%	42%	53%
Constant Equivalent Income, $\overline{x}_i(\alpha=2)$		1668	1312	1490	1687	1891	1954
% Shortfall from average income, α=2		35%	17%	22%	35%	46%	57%
Attock District	**107**						
Average Intertemporal Income		**2411**	**1262**	**1545**	**2172**	**2878**	**4052**
Constant Equivalent Income, $\overline{x}_i(\alpha=1)$		1607	1177	1454	1653	1851	1928
% Shortfall from average income, α=1		24%	0%	3%	21%	38%	55%
Constant Equivalent Income, $\overline{x}_i(\alpha=2)$		1436	1047	1165	1435	1719	1859
% Shortfall from average income, α=2		32%	8%	16%	31%	44%	61%

Table 8 (Continued)

Badin District	**130**						
Average Intertemporal Income		**2630**	**1461**	**1925**	**2439**	**3025**	**3833**
Constant Equivalent Income, $\overline{x}_i \left(\alpha = 1\right)$		1716	1358	1584	1785	1912	1953
% Shortfall from average income, α=1		27%	2%	13%	25%	39%	53%
Constant Equivalent Income, $\overline{x}_i \left(\alpha = 2\right)$		1576	1184	1398	1609	1823	1903
% Shortfall from average income, α=2		33%	11%	22%	30%	44%	56%
Dir District	**102**						
Average Intertemporal Income		**2646**	**1571**	**1959**	**2247**	**3055**	**4130**
Constant Equivalent Income, $\overline{x}_i \left(\alpha = 1\right)$		1720	1435	1600	1791	1875	1936
% Shortfall from average income, α=1		28%	6%	13%	25%	42%	56%
Constant Equivalent Income, $\overline{x}_i \left(\alpha = 2\right)$		1557	1195	1389	1576	1776	1856
% Shortfall from average income, α=2		35%	13%	22%	33%	46%	61%

Looking at the percentile distribution of the shortfall between constant equivalent income $\overline{x}_i$ and average income we see that the incomes of the richest, ever-poor households in the right-most column are most affected when we control for variability, dropping by between 54-59%. The shortfall for the top 25% in the second column from the right is 40-45%. The variability penalty drops monotonically as we move down the income distribution to near zero for the bottom 10 and 25% of the distribution. This is to be expected because in calculating the $\overline{x}_i$'s we excluded all incomes above the poverty line and the bottom percentiles are less likely to have ever had an income above z.

The general pattern of shortfalls at the district level is similar to the whole sample. The percentage shortfall of constant equivalent income is between 24 and 28% for α=1 and between 32 and 35% for α=2. Note, however, that the poverty ranking across districts can change if constant equivalent income is used instead of average intertemporal income. For example, Dir's average intertemporal household income of Rs2646 is higher than Badin's at Rs2630. However, when using constant equivalent income at α=2 then the ranking is reversed. This example illustrates that using a welfare measure that accounts for income variability can alter interregional poverty profiles.

Under the stability equivalent income approach there are two ways of measuring the social welfare cost of variability. First, we can compare the standard average income with the stability equivalent income. The percentage difference between the two shows the relative variability premium. Second, we can use the stability equivalent income to calculate FGT measures.[32] Unlike for the constant equivalent approach these poverty measures differ from the standard pooled cross section FGTs. Thus, we can compare them to get the cost of variability in terms of additional poverty.

For the applications below I use the Constant Relative Variability Aversion (CRVA) as shown in equation 14. This is the ex post analogue to the ex ante Constant Relative Risk Aversion (CRRA) utility functions in the risk literature. Initially, I set the coefficient of relative variability aversion ρ equal to 2. This baseline follows two previous studies which have tried to model vulnerability or variability (Ligon and Schechter (2003) and Cruces and Wodon (2003)) and is a common rule of thumb for CRRA functions. Under CRVA, as under CRRA, higher values of ρ imply greater reduction in welfare due to income variability. As an illustration of the magnitude of this effect on stability equivalent incomes and poverty measures I also present results for ρ =3 as well as for the two possible extremes when ρ=0 and when $\rho \to \infty$. For the initial applications reported below I assume δ=1, i.e., that there is no discounting of incomes.

[32] Note that FGT measures can be substituted by alternative poverty measures without loss of generality.

Table 9 compares average intertemporal income with stability equivalent income from equation 14 and reports the relative variability premium from equation 10. Note that these income estimates are not directly comparable with those in table 8 as here we can include all 667 households, not just the 421 who were ever poor.

For all districts together, the average relative variability premium is 18 and 24% for ρ equal to two and three, respectively. The welfare loss due to variability in table 9 tends to be more equally distributed across the income quantiles than is the case for constant equivalent income in table 8. But the richer households still tend to 'lose' a larger amount of income due to variability. However, unlike in the constant equivalent income approach, this is not a result of the evaluation function, but a reflection of the data; richer households experienced larger variations in incomes.

Table 9 Stability Equivalent Incomes and Percentage Shortfalls from Average Incomes

	Mean	**Percentile**				
		10%	**25%**	**50%**	**75%**	**90%**
All Districts						
Average Intertemporal Income, $x_{i(SE)}^{\rho=0}$	**3834**	**1342**	**1933**	**2950**	**4477**	**7149**
Stability Equivalent Income, $x_{i(SE)}^{\rho=2}$	3111	1251	1721	2555	3664	5516
Relative Variability Premium V_R, ρ=2	18%	4%	7%	13%	24%	39%
Stability Equivalent Income, $x_{i(SE)}^{\rho=3}$	2875	1082	1571	2376	3433	4975
Relative Variability Premium V_R, ρ=3	24%	6%	10%	19%	33%	51%
Stability Equivalent Income, $x_{i(SE)}^{\rho\to\infty}$	2002	655	1041	1648	2418	3590
Relative Variability Premium V_R, ρ→∞	47%	24%	32%	45%	58%	73%

Table 9 (Continued)

Faisalabad District						
Average Intertemporal Income, $x_{i(SE)}^{\rho=0}$	**4562**	**1804**	**2546**	**3437**	**4679**	**7374**
Stability Equivalent Income, $x_{i(SE)}^{\rho=2}$	3877	1536	2184	2981	3916	6072
Relative Variability Premium V_R, ρ=2	16%	4%	8%	13%	21%	30%
Stability Equivalent Income, $x_{i(SE)}^{\rho=3}$	3627	1372	1879	2782	3755	5697
Relative Variability Premium V_R, ρ=3	21%	7%	11%	18%	29%	39%
Stability Equivalent Income, $x_{i(SE)}^{\rho\to\infty}$	2563	881	1264	1896	2625	4102
Relative Variability Premium V_R, ρ→∞	44%	25%	32%	44%	54%	65%
Attock District						
Average Intertemporal Income, $x_{i(SE)}^{\rho=0}$	**3334**	**1319**	**1721**	**2582**	**3896**	**5996**
Stability Equivalent Income, $x_{i(SE)}^{\rho=2}$	2513	762	1312	2125	3211	4497
Relative Variability Premium V_R, ρ=2	22%	5%	7%	15%	28%	51%
Stability Equivalent Income, $x_{i(SE)}^{\rho=3}$	2289	607	1180	1914	2849	4158
Relative Variability Premium V_R, ρ=3	29%	7%	11%	22%	41%	62%
Stability Equivalent Income, $x_{i(SE)}^{\rho\to\infty}$	1551	337	707	1332	2006	3023
Relative Variability Premium V_R, ρ→∞	52%	25%	36%	50%	66%	80%
Badin District						
Average Intertemporal Income, $x_{i(SE)}^{\rho=0}$	**3688**	**1683**	**2270**	**3042**	**4415**	**6242**
Stability Equivalent Income, $x_{i(SE)}^{\rho=2}$	3061	1324	1837	2535	3819	5656
Relative Variability Premium V_R, ρ=2	17%	3%	7%	11%	22%	35%
Stability Equivalent Income, $x_{i(SE)}^{\rho=3}$	2838	1154	1625	2402	3521	5337
Relative Variability Premium V_R, ρ=3	22%	5%	9%	17%	30%	50%
Stability Equivalent Income, $x_{i(SE)}^{\rho\to\infty}$	1999	664	1102	1691	2473	3799
Relative Variability Premium V_R, ρ→∞	45%	23%	31%	43%	56%	75%
Dir District						
Average Intertemporal Income, $x_{i(SE)}^{\rho=0}$	**3823**	**1729**	**2189**	**2944**	**4550**	**7137**
Stability Equivalent Income, $x_{i(SE)}^{\rho=2}$	3027	1411	1733	2542	3424	5516
Relative Variability Premium V_R, ρ=2	18%	4%	7%	13%	25%	43%
Stability Equivalent Income, $x_{i(SE)}^{\rho=3}$	2776	1283	1585	2300	3258	4945
Relative Variability Premium V_R, ρ=3	25%	6%	11%	19%	33%	53%
Stability Equivalent Income, $x_{i(SE)}^{\rho\to\infty}$	1909	728	1040	1554	2403	3425
Relative Variability Premium V_R, ρ→∞	48%	25%	33%	48%	59%	73%

To illustrate the bounds of the effect of variability on income, consider the two extreme cases. In table 9, ρ=0 represents the baseline B case, hence, the relative variability premium is 0% and there is no loss of welfare compared to using average intertemporal income. Under the Rawlsian case when $\rho \to \infty$, the relevant measure is the minimum income for each household. As expected, the cost of variability is much higher, with a shortfall from average income of 47%.

Comparing districts, the income rankings of Badin and Dir again change depending on whether we penalize income variability. Of these two districts Dir has the higher average intertemporal income, but the lower stability equivalent income for any positive level of ρ.

In addition to presenting the welfare effect of income variability in terms of stability equivalent income we can also examine the effect of this variability on poverty measures directly. Table 10 shows rates of stability equivalent income poverty from equation 14 for the whole sample and the districts for three levels of α and for the same values of ρ as in table 9.

Again accounting for income variability has a large impact. As the coefficient of relative variability aversion ρ goes from zero to three the headcount index (α=0) increases by almost 17 percentage points - nearly doubling - for the entire sample. Since the poverty gap and squared poverty gap ratio are increasingly sensitive to the distribution of poverty the relative effect of income variability on these two poverty measure is even larger. Poverty for α=1 and α=2 increases three and four-fold as ρ goes from zero to three. Disaggregating by district, Badin and Dir again switch ranks.

Table 10 Poverty under Stability Equivalent Income for selected levels of ρ

	All Districts			Faisalabad			Attock		
	α=0	α=1	α=2	α=0	α=1	α=2	α=0	α=1	A=2
ρ=0	0.214	0.044	0.014	0.151	0.021	0.004	0.365	0.098	0.037
ρ=2	0.326	0.099	0.043	0.238	0.055	0.018	0.462	0.185	0.097
ρ=3	0.382	0.127	0.061	0.274	0.074	0.028	0.517	0.222	0.126
ρ→∞	0.642	0.265	0.147	0.573	0.186	0.090	0.768	0.385	0.241

	Badin			Dir		
	α=0	α=1	α=2	α=0	α=1	α=2
ρ=0	0.219	0.048	0.016	0.167	0.027	0.006
ρ=2	0.311	0.959	0.041	0.324	0.083	0.032
ρ=3	0.367	0.122	0.059	0.394	0.114	0.050
ρ→∞	0.630	0.255	0.140	0.632	0.260	0.139

4 The intertemporal distribution of poverty across households

This section proposes two new classes of poverty measures that account for the intertemporal distribution of poverty across households, derives a third one drawing on the unemployment literature, and compares these three with a fourth measure proposed by Basu and Nolen (2006) by applying them to the same data set from rural Pakistan.

Imagine two societies with the same amount of aggregate poverty over time, that is, they show the same amount of poverty in each time period. However, in the first society some households are permanently poor while the rest are never poor, while in the second society time spent in poverty is distributed equally across all households. The intertemporal income profiles for these two societies are depicted in figure 13. The arrows represent households i and j, z is the poverty line, x_{High} and x_{Low} are two income levels and t_1 and t_2 denote two time periods. (A) and (B) can be thought of as representing populations with only chronic and only transitory poverty, respectively.

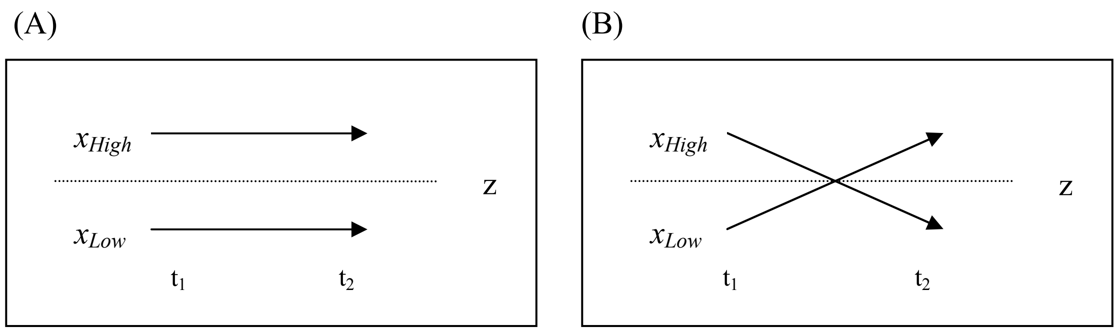

Figure 13 Two stylized intertemporal income distributions

How should the unequal intertemporal distribution of poverty be incorporated into a poverty measure and which society should it classify as being poorer? The answer and, thus, our choice of poverty measure, depends on our perspective and on the purpose for measuring poverty. From an individual's perspective, variability is bad, as in the previous section's discussion of the effect of income variability on household level poverty. However, from a societal perspective the intertemporal variability in households' incomes and, hence, the distribution of poverty across households and time can be good or bad. Sharing the burden of poverty over time across household and minimizing the level of chronic poverty is 'good' if we value social equity. This is the underlying motivation for all of the intertemporal poverty measures discussed in this section. In contrast, if the impact of experiencing poverty once is irreversible or if it is so severe that subsequent episodes of poverty have no further traumatic effect then the objective is to minimize the number of chronically poor households even at the expense of making already poor households even poorer. Only one of the four intertemporal poverty measures below can accommodate this objective.

Standard poverty measures, such as single-period FGTs aggregated over time, are insensitive towards the distribution of poverty across households over time and, hence, towards society's preference for such a distribution. As a result, these measures can give the same rate of poverty for quite different underlying distributions of poverty over time across households. For example, the FGTs for (A) and (B) are the same for t_1 and t_2 as well as for the aggregate of the two time periods.

Standard poverty measures can be made sensitive to the intertemporal distribution of poverty across households by choosing an appropriate method to aggregate lifetime household poverties (e.g., $SEIP_i$) or incomes (e.g., $x_{i(SE)}$) across households. There are two general approaches: i) discounting incomes[33] over time and ii) introducing an inequality dimension into the aggregate intertemporal poverty measure. The choice of method determines what types of distributional changes in the poverty burden are picked up, and the choice of parameters affects the degree to which aggregate intertemporal poverty in (B) differs from (A).

By discounting incomes over time we can construct a poverty measure which shows greater lower intertemporal poverty in society (B) than in (A). Let δ be the discount factor.[34] Then in (A) the two households i and j have lifetime incomes LI_i and LI_j of $y_1(1+\delta)$ and $y_2(1+\delta)$, respectively. In (B) they get $y_1+\delta y_2$ and $y_2+\delta y_1$. Hence, for $y_1 \neq y_2$

[33] Or poverty measures.
[34] Whether we take an ex ante perspective and look forward and discount future incomes, or evaluate ex post by looking back and discounting past incomes does not affect the following argument.

and δ>0 lifetime incomes are more equal in (B) than in (A), as both $y_1+\delta y_2$ and $y_2+\delta y_1$ lie strictly between $y_1(1+\delta)$ and $y_2(1+\delta)$. Hence, aggregate lifetime inequality of poverty[35] is greater in (A) than in (B). In matrix form this can be summarized as:

$$\underset{\sim}{y}+\delta M_A\underset{\sim}{y}=\underset{\sim}{y}(I+\delta M_A)=\begin{bmatrix}(1+\delta)y_1\\(1+\delta)y_2\end{bmatrix}, \text{ where } \underset{\sim}{y}=\begin{pmatrix}y_1\\y_2\end{pmatrix} \; and \; M_A=\begin{pmatrix}1&0\\0&1\end{pmatrix} \text{ for (A)}$$

and

$$\underset{\sim}{y}+\delta M_B\underset{\sim}{y}=\underset{\sim}{y}(I+\delta M_B)=\begin{bmatrix}y_1+\delta y_2\\y_2+\delta y_1\end{bmatrix}, \text{ where } \underset{\sim}{y}=\begin{pmatrix}y_1\\y_2\end{pmatrix} \; and \; M_B=\begin{pmatrix}0&1\\1&0\end{pmatrix} \text{ for (B).}$$

As δ increases, the difference in lifetime inequality of poverty between (A) and (B) gets larger. This can be seen intuitively by comparing the ratios of lifetime incomes in both situations. $(1+\delta)y_1/(1+\delta)y_2$ is independent of δ, whereas $y_1+\delta y_2/y_2+\delta y_1$ decreases in δ. More rigorously, (A) has a more unequal intertemporal distribution of poverty than (B) if M_B is more equal than M_A. That is true if and only if $\underset{\sim}{y}(I+\delta M_B)=M\underset{\sim}{y}(I+\delta M_A)$ such that M is bistochastic[36] (Conlisk 1989). As this needs to hold for all $\underset{\sim}{y}$ we need $I+\delta M_B=M(I+\delta M_A)$. Since $M_A=I$ this implies $I+\delta M_B=M\left(1+\delta\right)$. Hence we need to show that there exists a bistochastic matrix M such that $M=\frac{1}{1+\delta}\left(I+\delta M_B\right)$. Substituting M_B into this equation we get

$$M=\frac{1}{1+\delta}\left[\begin{bmatrix}1&0\\0&1\end{bmatrix}+\delta\begin{bmatrix}0&1\\1&0\end{bmatrix}\right]=\begin{bmatrix}\frac{1}{1+\delta}&\frac{\delta}{1+\delta}\\\frac{\delta}{1+\delta}&\frac{1}{1+\delta}\end{bmatrix}, \text{ which is clearly bistochastic.}^{37}$$

In assessing the intertemporal distribution of poverty it is important that our measure maintains household poverty histories for at least two reasons. First, in a normative sense, people may feel that being (very) poor in one period may be impossible to make

[35] In this simple example income inequality and poverty inequality are synonymous as we only have two income levels, one above and one below the poverty line.
[36] A bistochastic matrix is a square matrix whose elements are positive and whose rows and columns sum to one.
[37] And is a permutation matrix if δ=0.

up even through great riches in other periods. Second, even from a positive perspective poverty at one point can have irreversible effects on lifetime poverty. For example, low consumption in one period can lead to permanent disabilities. Poverty measures which capture such irreversible events are either discontinuous, e.g., Rawlsian in nature so that $P_{\alpha_i} = \min\left\{P_{\alpha_i}^t, t \in T\right\}$, or less extremely, put disproportionate weight on the worst periods, e.g., through a high value of *α*.

The need to preserve the poverty histories of households means that the anonymity axiom from poverty measurement applies only to entire poverty histories. For example, in situation (B) above the intertemporal poverty measure shouldn't be affected by which of the two households starts rich and which starts poor. The standard anonymity assumption holds in that sense. However, it *is* important that their respective lifetime poverty histories are maintained, as this is the only way we know that households have traded places. We could call this 'poverty history preserving anonymity'.

The discounting approach to measuring the effect of the intertemporal distribution of household poverties can be implemented as follows. First, introduce a discount factor to the lifetime income measure LI_i. We saw above that the resulting $LI_i(\delta)$ is greater than LP_i for any δ<1. The three FGT aggregate lifetime poverty measures *TLP(α=0,δ), TLP(α=1,δ) and TLP(α=2,δ)* can then be estimated using the suitably discounted poverty line $z = \sum_{t=1}^{T} \delta^{T-t} z_t$. The social welfare 'benefit' of more equally distributed lifetime household poverties is then the difference between the pooled cross section FGTs, and the *TLP(α,δ)*'s. The choice of δ represents society's preferences for the equality of lifetime household poverties. Higher levels of δ represent greater aversion to unequally distributed poverty, and more generally, to chronic poverty.

The second general way of incorporating the intertemporal distribution of poverty across households in an aggregate intertemporal poverty measures is by including an inequality dimension directly into the poverty measure. The two existing methods from the unemployment literature are discussed in the next section. Another method is proposed here and can be termed the 'poverty inequality aversion method'. It relies on using a convex function to aggregate individual households' lifetime poverty measures. Let ρ represent the degree of aversion to inequality of poverty across households. Then under constant relative poverty inequality aversion the aggregate intertemporal poverty measure can be expressed as:

$$P(\rho)=\begin{cases}\left[\dfrac{1}{N}\sum_{i=1}^{N}LP_i(\alpha)^{\frac{1}{1-\rho}}\right]^{1-\rho} & if\ \rho\neq 1\\ \sqrt[N]{\prod_{i=1}^{N}LP_i(\alpha)} & if\ \rho=1\end{cases} \tag{15}$$

Equation 15 has two sources of curvature through parameters ρ and α. ρ accounts for the inequality of lifetime poverties across households. Setting $\rho>1$ makes $P(\rho)$ convex in individual household lifetime poverties $LP_i(\alpha)$. Hence, for a given level of aggregate intertemporal income, the policy response for reducing overall intertemporal poverty would be to equalize lifetime poverties. The level of α determines the extent to which we penalize the unequal distribution of poverty over time for a single household.

$P(\rho)$ in equation 15 becomes concave when the exponents are switched. A concave aggregation function is appropriate when instead of penalizing the inequality of poverty across households we want to reward it. Among the four measures that account for the intertemporal distribution of poverty across households the poverty inequality aversion measure is the only measure that can either penalize or reward inequality of poverty.

Existing studies on the intertemporal distribution of 'bads' across households

Two other methods of accounting for the inequality of poverty or other societal bads have been proposed in the existing literature: Basu and Nolen's (2006) measure for unemployment and poverty, and Borooah's (2002) measure for unemployment. In contrast to the poverty inequality aversion method proposed above these two methods can only treat inequality of 'bads' as a negative.

Basu and Nolen (2006) is the only paper to date which includes something akin to a 'churning axiom' which rewards zero-sum symmetric income mobility. Their proposed poverty measure treats intertemporal mobility as a 'good' via a Rawlsian-style multiplicative aggregation function:

$$P^{\beta}(p_1, p_2 ..., p_n) \equiv \frac{1}{\beta} - \prod_{i=1}^{n} \left(\frac{1}{\beta} - p_i \right)^{\frac{1}{n}} \qquad (16)$$

where p_i is household i's intertemporal poverty measure, $P(p_1, p_2 ..., p_n)$ is the poverty profile of the society, and $\beta \in (0,1)$ is a poverty aversion parameter. When using the headcount index, p_i represents the proportion of time household i is poor. If poverty is shared equally among all people then $p_i = p_j \ \forall p_i, p_j \in P$, and the effective poverty rate is the regular FGT measure for any value of β. In the (excluded) limiting cases we have the regular FGT (i.e., a utilitarian poverty measure) when β=0, and a Rawlsian poverty measure (where poverty is at its maximum as soon as one person is poor) if β=1. Thus by choosing β we can decide how much to value a more intertemporally equal distribution of poverty.

The Basu-Nolen measure cannot be separated into its poverty and mobility dimensions. Mobility, and hence the equality of poverty durations, is included through the multiplicative method of aggregation. Basu and Nolen also explicitly reject separability of the measure into the poverty levels of individuals for two reasons. First, it allows the sensitivity of the aggregate poverty measure to a change in any individual's poverty to vary inversely with the aggregate level of poverty in the society. This of course is desirable only if we accept that the marginal effect of a household getting poorer is greater in a richer society than in a poorer one. Second, they argue that poverty cannot be equated to pure welfarism. Basu and Nolen (2004) defend their 'non-welfarist' approach arguing that it is possible that people near the poverty line are not risk averse. While this may be true under certain circumstances, particularly when there are non-linearities and threshold effects in welfare dynamics, it seems contrary to the findings in much of the literature on poverty and risk. The Basu-Nolen poverty measure can include depth and severity of poverty by choosing p_i to be i's $P_{\alpha=1}$ or $P_{\alpha=2}$ history.

Borooah (2002) introduces a different approach for including inequality into an unemployment measure. Here I draw on his 'duration sensitive' unemployment measure to define a measure of poverty which is responsive to how much aggregate intertemporal poverty is shared within a population. Let d_i be the number of periods household i is poor. $d_i \in [0,T]$, where T is the number of periods observed. Let p_i be the proportion of periods in which i is poor so that $p_i=d_i/T$, and the average duration of poverty is $\overline{d} = T\overline{p}$, where $\overline{d} = \frac{1}{N}\sum_{i=1}^{N} d_i$. Poverty is equally shared in society if $d_i=d_j$ for all $i, j \in N$. If the same number of households (not necessarily the same households) are poor in each period, the headcount index H_0 is the same for all t in T. And the average duration of poverty is $\overline{d} = TH_0$.

Then define an additively separable social loss function $L = \sum_{i=1}^{N} F(d_i)$, where $F(d_i)$ is the social loss due to i's duration of poverty. Then the change in L from a change in d_i is: $\Delta L = \sum_{i=1}^{N} \partial F(d_i)/\partial d_i \Delta d_i$. If $F(.)$ is strictly convex, then the social marginal loss, $\partial F(d_i)/\partial d_i$, is increasing in d_i. Thus, the loss to society gets larger as any individual's spell in poverty d_i increases. Hence, for an average duration of poverty $\overline{d}$, L is minimized if $d_i=d_j$ for all $i, j \in N$. If $F(.)$ is defined as a constant elasticity function, then its elasticity ε represents society's aversion against unequal distribution of poverty duration and can be chosen as desired.

The Borooah-based method also introduces a natural way to handle the trade-off in the poverty measure between greater equality of the duration of poverty and higher poverty incidence. Let a richer household k give something to a poorer household j so that $\Delta d_k = -\Delta d_j$ *and* $\Delta d_i = 0, i \neq j, k$, and average poverty duration $\overline{d}$ remains constant. Let $d_j = \lambda d_k, \lambda > 1$. Then the transfer of poverty duration from k to j results in a change in social loss of:
$\Delta L = \partial F(d_k)/\partial d_k \Delta d_k - \partial F(d_j)/\partial d_j \Delta d_j = d_k^{\varepsilon} \Delta d_k - \lambda^{\varepsilon} d_k^{\varepsilon} \Delta d_j$. If ΔL=0, i.e., the transfer didn't change social loss, then $\Delta d_k = \lambda^{\varepsilon} \Delta d_j$. If ε=0 then the transfer of poverty

duration could be done without increasing the average duration of poverty $\overline{d}$. This is what standard poverty measures assume implicitly. If, however, ε>0 then society would be willing to increase *k*'s poverty duration by more than the reduction in *j*'s duration: $\Delta d_k = \lambda^{\varepsilon} \Delta d_j > \Delta d_j$.

Finally, we can define a duration-adjusted poverty rate. Recall $\overline{d}$ is the actual average duration of poverty. Then, let *d** be the average poverty duration when poverty duration is equally distributed where *d** and $\overline{d}$ have the same social loss. Then $d^* \geq \overline{d}$. In the terminology of the Atkinson poverty index, *d** is the equally distributed equivalent poverty duration. Applying Atkinson's index to the inequality in poverty duration gives:

$$A_{\varepsilon} = (d^*/\overline{d}) - 1 = \left[\sum N^{-1} \left(\frac{d_i}{\overline{d}} \right)^{1+\varepsilon} \right]^{1/(1+\varepsilon)} - 1 \tag{17}$$

A_{ε} measures how far away the actual distribution of intertemporal poverty across households is from perfect equality, with parameter ε determining the sensitivity to inequality of poverty. ε=0 means that society is indifferent to the distribution of poverty durations across households, so that $d^* = \overline{d}$ and $A_0 = 0$. For a given $\overline{d}$>0, *d** and A_{ε} increase as ε rises. Thus, the social loss from $\overline{d}$ is $L = d^* = \overline{d}(1 + A_{\varepsilon})$.

Now we can use the analog principle to apply this to poverty measurement. Let H_0^* and $\overline{H_0}$ denote the duration adjusted poverty headcount index and the standard headcount index, respectively. Then H_0^* can be expressed as a function of $\overline{H_0}$ and the distribution of the duration of poverty A_t.

$$\overline{H_0}(1+A_\varepsilon) = H_0^* \qquad (18)$$

This method can be used in a similar fashion to calculate the Atkinson measure and the social welfare loss function due to the unequal distribution of poverty depth and severity by replacing poverty duration, i.e., $LP_i(0)$, with the intertemporal averages of poverty depth and severity, i.e., $LP_i(1)$ and $LP_i(2)$.

Estimating the effect of the intertemporal distribution of poverty

Table 11 presents results for the four different methods of adjusting poverty rates for the intertemporal distribution of poverty across households. As before results are provided for the whole sample and for each district. Again, absent any benchmarks for these new extensions to standard poverty measures, including the districts individually shows to what extent different methods of accounting for the intertemporal distribution of poverty can affect poverty rankings.

First, let us look at the results for the headcount index for all districts in the first column of Table 11. Poverty rates for the discounting method are shown for four different discount rates. The case of δ=1 is the same as the average income case from Baseline B. To test the sensitivity of the poverty measure to the choice of δ table 11 also presents results for discount rates of 0.9, 0.5, and 0.1. First, note that as δ increases so do the poverty indices for all districts combined as well as for individual districts. This is as expected as we have shown that decreases in δ increase the inequality of poverty. Hence, any poverty index adjusted for the intertemporal distribution of poverty by discounting incomes should also go up. As past incomes are discounted more and δ falls to 0.9, 0.5 and 0.1, poverty headcounts for all districts increase to by 1, 8 and 15 percentage points compared to the baseline of $\delta = 1$. $P_{\alpha=1}$ and $P_{\alpha=2}$ increase even more as δ falls as they are increasingly more sensitive to the distribution of poverty.

For the Basu and Nolen method we have to pick a value for the poverty inequality aversion parameter β. β has to lie between zero, the case of the utilitarian measure from the pooled cross section in Baseline A, and one, the Rawlsian case. Choosing the mid point 0.5 seems a natural first choice. Another choice is to use the level of β that corresponds to the following value judgment: A society that in which half the people are always poor and the other half is always non-poor is deemed to have the same poverty as a society in which everyone is poor three quarters of the time. Basu and Nolen (2006) show that this level of β is 8/9.[38] As shown in Table 11, these two levels of poverty inequality aversion increase the poverty headcount index for all districts by between 2 and 11 percentage points compared to baseline A represented by the case $\beta = 0$.

For the Borooah-based method we first need to choose a value of ε, where $\varepsilon \in [0, \infty)$. The lower bound indicates no aversion to inequality of poverty and infinity is the limiting case of total aversion to inequality, meaning that aggregate poverty rates are equal to those of the poorest household. I started by picking 0.5 and 2, which are commonly used values for the Atkinson index.[39] As ε increases all P_α's increase monotonically, by between 6 and 20 percentage points, which is slightly more than for the other two methods. Under the poverty inequality aversion method headcount

[38] For justification see Basu and Nolen (2004).
[39] Note though that these are common values when measuring the inequality of income or consumption. There are no common values of aversion for the Atkinson index applied to the distribution of poverty as this paper is the first such application.

Table 11 FGT Poverty Rates adjusted for the intertemporal distribution of poverty across households

	All Districts			Faisalabad			Attock			Badin			Dir		
	α=0	α=1	α=2	α=0	α=1	α=2	α=0	α=1	α=2	α=0	α=1	α=2	α=0	α=1	α=2
Discounting Method															
δ=1	0.214	0.044	0.014	0.150	0.020	0.004	0.361	0.097	0.038	0.221	0.049	0.017	0.167	0.027	0.006
δ=0.9	0.226	0.047	0.015	0.150	0.021	0.004	0.346	0.097	0.038	0.239	0.053	0.018	0.198	0.032	0.008
δ=0.5	0.293	0.074	0.027	0.165	0.028	0.006	0.342	0.102	0.046	0.332	0.090	0.034	0.313	0.073	0.024
δ=0.1	0.360	0.124	0.058	0.211	0.050	0.017	0.365	0.115	0.061	0.440	0.157	0.075	0.378	0.145	0.069
Basu & Nolen Method															
β=0	0.296	0.096	0.046	0.234	0.061	0.025	0.413	0.151	0.081	0.305	0.091	0.041	0.264	0.086	0.040
β=0.5	0.320	0.097	0.046	0.245	0.061	0.025	0.435	0.153	0.082	0.311	0.095	0.042	0.293	0.089	0.041
β=8/9	0.373	0.101	0.047	0.275	0.063	0.025	0.511	0.161	0.085	0.364	0.096	0.044	0.334	0.092	0.041
Borooah-based Method															
ε=0	0.296	0.096	0.046	0.234	0.061	0.025	0.413	0.151	0.081	0.305	0.096	0.044	0.264	0.086	0.040
ε=0.5	0.362	0.127	0.067	0.291	0.084	0.039	0.467	0.288	0.190	0.355	0.120	0.057	0.336	0.102	0.049
ε=2	0.497	0.200	0.121	0.414	0.137	0.071	0.599	0.415	0.305	0.491	0.190	0.101	0.462	0.152	0.082
Poverty Inequality Aversion															
ρ=0	0.296	0.096	0.046	0.234	0.061	0.025	0.413	0.151	0.081	0.305	0.096	0.044	0.264	0.086	0.040
ρ=0.25	0.347	0.118	0.060	0.281	0.079	0.035	0.461	0.178	0.100	0.357	0.120	0.059	0.309	0.104	0.051
ρ=0.5	0.421	0.156	0.086	0.350	0.107	0.051	0.535	0.221	0.135	0.433	0.159	0.084	0.376	0.134	0.070
Memorandum															
Gini Coefficient of Lifetime Poverties	0.55	0.65	0.72	0.59	0.71	0.78	0.47	0.56	0.64	0.56	0.66	0.74	0.56	0.63	0.69

indices increase with the inequality aversion factor ρ by between 5 and 12 percentage points.

The effect of accounting for the intertemporal distribution of poverty on the poverty gap and the squared poverty gap indices for all districts is shown in columns 2 and 3 in Table 11. As the level of α increases the effect of accounting for the distribution of poverty across households becomes stronger. This is because lifetime household poverties are increasingly unequally distributed as α rises, as seen in the last row of Table 11.

The Basu and Nolen measure has never been applied to poverty measurement, the Borooh-based measure is adapted for poverty measurement in this paper, and the other two measures are new altogether. Given this newness and in the absence of clear benchmarks for choosing the poverty inequality aversion parameters in each measure, it is useful to examine how these different measures affect results across districts.

Table 11 shows that poverty rates increase in all cases. However, the different methods of accounting for the intertemporal distribution of poverty across households affect districts' poverty rates to different extents. Faisalabad and Attock provide a useful comparison as they represent the most and least unequal district in terms of the distribution of lifetime household poverties (see last row in Table 11).

For example, for all levels of α increasing the inequality parameter in the discount method has a larger absolute and relative impact on poverty estimates for Faisalabad than for Attock. In contrast, percentage increases in poverty estimates resulting from an increase in ρ is similar for both districts under the poverty inequality aversion method, while under the Borooah-based method the percentage increase in poverty estimates is greater for less unequal Attock. Unlike the other measures the Basu and Nolen measure is relatively unaffected by changes in the inequality parameter for the headcount index, and even more so for the distributionally more sensitive poverty gap and squared poverty gap. These comparisons across methods and different levels of poverty inequality aversion clearly show that accounting for the intertemporal distribution of poverty affects aggregate poverty measures, and that the choice of how to explicitly account for it matters. It also highlights the effect of relying on traditional static poverty measures with their implicit assumption that the distribution of poverty across households over time does not matter.

Table 12 reports the Atkinson index for the inequality of poverty durations for the three P_α's and for two values of ε. The Atkinson index in general measures how far a distribution is from perfect equality. In this context the index can be interpreted as the 'intertemporal poverty premium' of the inequality of poverty durations. In other words, it shows the percentage increase in the P_α indices resulting from the actually existing unequal distribution of poverty spells.

The increase in the intertemporal poverty measure due to the unequal distribution of poverty over time appears quite large regardless of our choice of ε. For all districts combined, even the relatively low value of 0.5 (at least low compared to estimates of ε based on consumer preferences) causes the 'poverty distribution corrected' headcount to increase by 22 percent. Put differently, redistributing time spent in poverty equally across the population, while keeping aggregate income unchanged, would reduce headcount poverty by 22 percent. Looking at it this way the 22 percent actually seem small. Ultimately, choosing the level of the intertemporal poverty premium is a normative choice. The same, of course, is true for choosing δ for the discount method, or β for Basu and Nolen's measure. If one considers such a normative choice undesirable, one should keep that traditional poverty measure also make such a normative choice, albeit implicitly: by default the intertemporal distribution of poverty is assumed not to matter!

Table 12 Intertemporal Poverty Premium due to the Unequal Intertemporal Distribution of Poverty

	All Districts			Faisalabad			Attock		
	α=0	**α=1**	**α=2**	**α=0**	**α=1**	**α=2**	**α=0**	**α=1**	**α=2**
ε=0.5	22%	32%	46%	24%	39%	54%	13%	91%	134%
ε=2	68%	108%	164%	77%	125%	183%	45%	175%	276%

	Badin			Dir		
	α=0	**α=1**	**α=2**	**α=0**	**α=1**	**α=2**
ε=0.5	16%	25%	31%	27%	19%	24%
ε=2	61%	98%	130%	75%	77%	105%

When disaggregated by district the intertemporal poverty premium varies considerably. The poorest district, Attock, is also most uniformly poor, as evidenced by the lowest intertemporal poverty premia for the headcount ratio (α=0). In contrast, poverty in the richest district, peri-urban Faisalabad, is least equitably distributed.

5 Conclusions

This paper has proposed new classes of poverty measures that extend standard static FGT indicators to account for two dynamic aspects that influence household and societal welfare: the variability over time of individual household incomes and the intertemporal distribution of poverty across households.

Economic theory, if not common sense, tells us that income variability is undesirable as it reduces overall intertemporal household welfare. Thus, measures of poverty that capture the effect of variability are conceptually superior to standard poverty measures for characterizing poverty over time. This paper has outlined two different ways how variability can be incorporated into household income measures and, by extension, into poverty indices. It has also presented some results for rural Pakistan comparing the two methods and their sensitivity towards the choice of parameters (δ, ρ).

In practice, the choice of method and the selection of the variability aversion parameters will depend on the policy issue at hand. If the emphasis is on minimizing the number of households that have to endure poverty then household lifetime poverty should be measured using constant equivalent income. This would be appropriate in either of two circumstances. First, households can never (fully) recover from periods spent in poverty, for example in terms of physical irreversibilities or social stigma or second, if moving out of poverty again is disproportionately difficult or costly due to non-linearities and threshold effects in welfare dynamics. In contrast, if the main policy focus is on minimizing the social welfare loss due to income variability regardless of whether these income fluctuations cause households to move in and out of poverty over time, then using stability equivalent income would be the appropriate income indicator.

It is also worth noting that the choice of method, and indeed the choice of parameters, not only depends on the particular policy focus, but also on the value judgment of the evaluator. Of course, economists tend not to be fond of value judgments, but if we are interested in social welfare some of these judgments are unavoidable. Indeed, without them it would be difficult to assess the social welfare consequences of income variability. In practice, value judgments are often made implicitly in assessing social welfare, e.g., by choosing to use, say, the Gini coefficient over the Theil index in measuring inequality changes, or by selecting our preferred level of α for evaluating poverty trends. Thus, since some degree of value judgment is necessary in welfare economics, it is better to make it explicit.

Empirically, the range of welfare losses for the two different methods are similar when looking at average variability adjusted incomes. Using the constant equivalent income method observed variability reduces Pakistani household welfare by as much as a third. Under the stability equivalent method this effect is between one-fifth and a quarter of average income, for ρ=2 and 3. At the Rawlsian extreme, which counts only households' lowest incomes, the welfare loss due to variability is around half of average income. Furthermore, the comparison across districts showed that both methods of accounting for income variability can change poverty rankings. If resources are allocated according to these rankings, using welfare indicators that explicitly account for variability instead of the standard, static poverty measures can have important practical implications.

Looking beyond income averages, the two methods differ systematically in how accounting for income variability affects different quantiles of the income distribution. Under the constant equivalent income approach, the shortfall from average incomes increases negligibly for the bottom 10% of the income distribution but by close to half for the richest 'ever-poor' households. The social welfare cost from income fluctuations is, thus, highest for households that are only temporarily poor, i.e., households that would never experience poverty if their incomes were more stable.

Clearly, the position of the poverty line is key in using the constant equivalent income approach.

Indeed, the analytically most insightful positioning would not be at the official poverty line, but at a dynamic poverty threshold (if one exists). A dynamic poverty threshold in this context represents an unstable dynamic welfare equilibrium below which households would not be expected to climb out of poverty without assistance.[40] Placing the poverty line for the constant equivalent income welfare measure at such a threshold point would assign the greatest long-term social welfare cost from income variability to those households that fall below the threshold and into a poverty trap over time. In contrast, income fluctuations for households that were always poor are less 'costly' in terms of social welfare as, by not having crossed a threshold, the cost of getting them out of poverty has not increased as a result of income variability. Thus, in the presence of threshold effects below the poverty line the constant equivalent income measure can be a useful indicator for effective targeting of social safety nets and economic development programs.

The stability equivalent income approach, in contrast, is most appropriate if we want to penalize income fluctuations equally across the entire income distribution. The calculated shortfalls from average incomes show only a slight rise across the income distribution, suggesting that richer households had larger fluctuations relative to their income level[41], though these differences are small and decrease as the coefficient of relative variability aversion rises.

[40] See Carter and Barrett (2006) for a detailed model of nonlinear welfare dynamics with dynamic threshold points.
[41] Perhaps some of this is due to greater measurement error for larger incomes.

The costs of income variability in terms of poverty can only be calculated for the stability equivalent income approach. For $\rho=2$ and 3 this results in an increase in the headcount index of 11 and 17 percentage points. The Rawlsian case would almost triple headcount income poverty, reflecting the large income fluctuations in the survey.

This paper has also proposed two new methods for adjusting poverty indices to take account of the intertemporal distribution of poverty across households and derived another method from Borroah's (2002) paper on unemployment. It compared these three methods and the Basu and Nolen's (2006) measure by applying them to the same PRHS dataset. Each method requires choosing a parameter representing society's preferences towards the intertemporal distribution of poverty which in turn influences the inequality-adjusted poverty rates.

Looking at the poverty estimates for a broad range of parameters, the effect of the intertemporal distribution of poverty is similar in magnitude for the discounting method, the Basu and Nolen method and the poverty inequality aversion method, with percentage point increases in poverty of up to 15. The Borooah-based method appears to weight the intertemporal distribution of poverty more. At $\varepsilon=2$ the adjusted poverty rates are already higher than for the highest parameters for the other methods, and ε can be raised to infinity. As with the variability adjusted poverty measures earlier, the choice of method for accounting for the intertemporal distribution of poverty across households depends on the particular application of interest as well as preferences for evaluating social welfare.

Finally, while the paper has treated the two dynamic extensions to static poverty measures separately, they can conceivably be combined. Individual household poverty over time can be calculated taking account of intertemporal variation. The resulting household lifetime poverty or income measures can then be aggregated through one of the concave aggregation techniques that account for the intertemporal distribution of poverty across households.

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Chapter 5:
Microeconomic Determinants of Income Inequality in Rural Pakistan

1 Introduction

Poverty reduction policies after the Washington consensus have largely focused on fostering economic growth. However, since the late 1990s income distribution has been 'brought back in from the cold' (Atkinson 1997) and is making its way back onto the international policy agenda (Kanbur and Lustig 1999). This renewed interest in inequality is due to the emerging consensus that income inequality has an important influence on poverty reduction, both in theory and in practice (for an overview see Fields (2001)). This works through two main channels. First, the degree of inequality directly determines how a given amount of economic growth is shared among all members of society across the entire income distribution. Second, inequality can have an indirect impact on poverty reduction by reducing the amount of economic growth itself.

Given that income inequality matters for reducing poverty it is surprising how little is known about the determinants of the level of income inequality and, even more so, about the determinants of changes in the distribution of income (Kanbur 2000). Such knowledge would be highly relevant for policy purposes as it would enable policy makers to decide whether and how to take action.[42] For example, knowing what factors determine income inequality would highlight whether existing inequalities are

[42] These decisions should ideally depend on whether inequalities are deemed to be instrumental, for example resulting from rewards to risk-taking, enterprise, education or savings, or dysfunctional, for instance due to political connections, discrimination or inheritance (Killick 2002).

due to intrinsic unchangeable characteristics, such as location or ethnicity, or due to variables whose distribution can be changed through policy, for instance, through broadening access to education. In sum, gaining better insights into the determinants of inequality would help to assess the distributional effects of existing and new poverty reduction and growth policies. This is relevant not only for policies specifically aimed at making the distribution of income more equitable, but also for assessing whether any proposed new policy is likely to affect the distribution of income via impacts on the distribution and returns of the determinants of income inequality.

Pakistan provides an interesting case study for examining the determinants of income inequality. High poverty rates, particularly in rural areas, make poverty reduction imperative. However, the extent to which overall economic growth has reduced poverty depended greatly on concurrent changes in the distribution of income. During the second half of the1980s relatively fast growth in agricultural output substantially reduced poverty. In contrast, even higher rates of agricultural growth during the 1990s have bypassed many poor (World Bank 2002) because growth was accompanied by an increasingly unequal distribution of income. This suggests that to reduce poverty effectively in rural Pakistan it is important to look beyond the growth dimension and gain a better understanding of underlying structure of income inequality; in particular, to examine what factors determine the level of income inequality, what drives changes in the distribution of income, and whether these changes are due to changes in the distribution or due to changes in the returns to particular factors. As yet, there have been no attempts to disentangle these dynamic issues although this can provide important insights to make poverty reduction policies more effective.

Inequality decomposition studies on Pakistan to date have relied on traditional decomposition techniques and were, thus, unable to explore the. For the 1970s de Kruijk and van Leeuwen (1985) and de Kruijk (1987) conclude that inequality was rising due to non-labor income and 'other sources of income', mainly remittances. Labor income was the most important source of inequality. However, since labor income accounted for 80 per cent of income but only 60 per cent of the Theil index, increases in labor income were actually inequality reducing. Land and property income became less important as source for inequality, even in rural areas. Spatial factors and variations across occupation groups were only minor sources of inequality.

Studies by Adams and co-authors (Adams and Alderman 1992; Adams 1994; Adams and He 1995) decompose income inequality in the late 1980s, identifying agricultural income as main source of inequality, accounting for between 27 to 46 per cent of total inequality. Further decomposing agricultural income they conclude that land ownership alone accounted for between a third and a half of total inequality, with labor and crop profits accounting for the other half of agricultural income inequality. Income from livestock and from non-farm activities was more important for the poor, and hence tended to reduce inequality. However, as is typical for these types of income source decompositions, Adams and co-authors find that non-farm income, transfers, and rentals either increased or reduced inequality, depending on the inequality index used.

This paper goes beyond the existing static inequality decompositions and examines the drivers of inequality in a dynamic context and in terms of variables that are more relevant for policy. For this purpose it adapts a regression-based inequality decomposition technique which possesses a number of important advantages over traditional inequality decompositions by income source (Shorrocks 1982) or by sub-group(Shorrocks 1984). Most importantly, it allows patterns and changes in inequality to be analyzed not in terms of outcomes, but in terms of the drivers of these outcomes. Traditional inequality decompositions are primarily descriptive. They can tell us what types of incomes or sub-groups account for inequality, but since by design their analysis does not incorporate household endowments and characteristics, their conclusions tend to remain vague as to whether and how to address income inequality.

This paper uses the same data as the studies by Adams and co-authors. Therefore, it can, in a familiar setting, examine the dynamics and the root causes of income inequality. For example, the dynamic analysis finds that higher education has made the distribution of income more equal over time. While an interesting finding in itself, the more relevant insight is that this took place because access to higher education has become more equal, despite the simultaneous inequality-raising effect of increases in returns to higher education.

The next section provides a brief overview of existing approaches to analyzing income inequality. Section 3 lays out the decomposition methodology used in this study. The data are introduced in Section 4. The results from the econometric analysis in section 5 describe the determinants of the level of, and changes in, income inequality, and describe to what extent changes in inequality over time are due to changes in the distribution of factors versus changes in factor returns. Section 6 concludes.

2 Existing approaches to explaining inequality

To date poverty and inequality research has tended to focus on the link between growth and poverty reduction, the impact of growth on inequality, and the impact of inequality on growth. In contrast, there have been far fewer attempts to explain the factors that influence the distribution of income. One strand of the inequality literature has tried to explain theoretically why inequality exists and persists. These studies have tried to model the link between income inequality and asset inequality or credit market imperfections (Banerjee and Newman 1993; Galor and Zeira 1993).

A second, applied strand of the literature uses one of two inequality decomposition techniques: decomposition by income source following Fei *et al.* (1978), Pyatt *et al.* (1980) and Shorrocks (1982); and decomposition by population sub-group in the tradition of Blinder (1973), Oaxaca (1973) and Shorrocks (1984). Most existing country studies on the determinants of inequality apply these techniques, including all existing studies on Pakistan (de Kruijk 1987; Adams and Alderman 1992; Adams 1994; Adams and He 1995). The analysis in both of these types of decomposition studies is statistical in nature. By construction they have to exclude a range of variables, which are likely to matter and which policy can influence. For instance, the decomposition by income source can help to identify how much of income inequality is due to, say, agricultural income, non-agricultural income, rent, and transfers. However, it cannot assess how other important factors such as household composition, human capital or location influence income inequality. Similarly, decomposition by subgroup can display how income varies between certain subpopulations, but it does not indicate why it varies.

These two strands of the inequality literature have left a gap between the statistical analysis of inequality on the one hand and economic theories of its causes on the other. A small but growing number of studies has aimed to bridge that divide using a regression-based technique developed and refined by Fields (2003)[43], Ravallion and Chen (1999) and Heltberg (2003). This technique combines income regression analysis with Shorrocks-type income source decomposition, where the ‘income sources’ in the second stage decomposition analysis are determined by the first stage income regression. This technique allows us to go beyond decomposing inequality changes simply in terms of income components and subgroups. Instead, we can explain inequality by any factor that can be included in an income or consumption regression, including variables that are relevant for policy. This enables us to explore two key areas where our understanding of inequality is weak (Kanbur 2000): the causes of inequality at country level; and inequality, and its causes, at different levels of aggregation between broadly defined groups, for example by household demographics, education, region, or ethnic group.

3 Methodology

The regression-based inequality decomposition proposed by Fields (2003) allows us to assess how much inequality at one point in time is explained by each determinant. In addition, changes in inequality over time can be decomposed into those resulting from changes in the distribution of individual determinants and those which come about due to changes in the returns to each determinant.

[43] It first appeared in 1995 in a working paper by Gary Fields entitled “Accounting for Changing Wage Inequality”.

Determinants of the level of inequality

The first step towards estimating the determinants of income inequality is to estimate the determinants of income using a standard income regression

$$\ln \mathbf{y} = \boldsymbol{\alpha} + \mathbf{X}\boldsymbol{\beta} + \varepsilon \tag{1}$$

where ln **y** is the *N*-vector of the logarithm household income per adult equivalent, **α** is the intercept, **X** is the NxK matrix of *k* household characteristics, and **ε** is the normally distributed error term $\varepsilon \sim N(0, \sigma_\varepsilon^2)$. Following common practice with these types of income equations I use a linear model with a semi-log specification, and include as regressors variables which help to describe a household's ability to earn income. These include variables on household demographics, assets, education and location.

Some of these covariates of income may be considered endogenous, certainly over longer time periods. For example, household size is affected by migration decisions, and the level of household assets and education depends on the household's own decisions. However, it is unclear what instruments I could use for these. Moreover, since the period of analysis spans only three years I treat all household characteristics as exogenous.

The second step is to use the estimates from the regressions to construct factor inequality weights for each variable in the regression. This is done by exploiting the analogy to Shorrocks' (1982) inequality decomposition by income source, which has shown that income inequality can be decomposed into its *K* factors such that:

$$s_k = \frac{\operatorname{cov}(y_k, y)}{\sigma_y^2}, \qquad \sum_{k=1}^{K} s_k = 1, \qquad \sum_{k=1}^{K} y_k = y \tag{2}$$

where $\operatorname{cov}(y_k, y)$ is the covariance between income from factor k and total income, and σ_y^2 is the variance of total income. s_k represents the proportion of income inequality due to source k, or the relative factor inequality weight of factor k. The sum of all s_k's adds up to one, and the sum of all K income sources equals total income.

Following Fields (2003) we can replace the y_k in equation 2 with household characteristic x_k's predicted contribution to total household income from equation 1, $\hat{\beta}_k x_k$. Then, the relative factor inequality weight of x_k is given by equation 3.

$$s_k = \frac{\operatorname{cov}(\hat{\beta}_k x_k, y)}{\sigma_y^2} = \frac{\hat{\beta}_k \operatorname{cov}(x_k, y)}{\sigma_y^2} = \frac{\hat{\beta}_k \sigma_{x_k} \rho(x_k, y)}{\sigma_y} \tag{3}$$

In practice, it is most convenient to use the middle expression of equation 3. Then, the s_k's can be computed by multiplying their respective $\hat{\beta}_k$ from equation 1 by the coefficient obtained by an OLS regression of the respective x_k on log income (Ravallion and Chen 1999). The relative factor inequality weight has the following interpretation: inequality increases for any factor with a positive s_k, it decreases for s_k negative, and remains unchanged for factors with s_k=0. The factor inequality weight corresponding to the error term of the regression, ε, identifies the proportion of inequality unexplained by the variables included in income regression 1. s_ε is calculated analogously to the other s_k's. Therefore,

$$s_{\varepsilon} = \frac{\operatorname{cov}(\varepsilon, y)}{\sigma_y^2} = 1 - R^2 \qquad \text{and} \qquad \sum_{k=1}^{K} s_k = R^2 \tag{4}$$

Equation 4 shows that the explanatory power of the regression determines the proportion of inequality that can be explained. Put differently, any analysis of income inequality and its changes is only as meaningful as the underlying income regression.

To gauge the proportion of explained inequality that is due to factor *k* we can calculate the percentage contribution or 'p weights', p_k, which are simply the factor inequality weight divided by the R squared of the regression (Fields 2003): $p_k = \frac{s_k}{R^2}$.

Compared to other methods of inequality decomposition this regression based decomposition technique possesses a number of advantages (Fields 2003; Heltberg 2003) that make it more versatile, and potentially insightful, for policy purposes. First, it is not limited to predetermined income sources. Instead, inequality can be decomposed into any factor explained by an income regression. Second, it makes it easy to combine the relative factor inequality weights of a subset of variables into a single group factor inequality weight, s_g, as shown in equation 5.

$$s_g = \sum_{k \in g} s_k = \frac{\operatorname{cov}(\sum_{k \in g} \hat{\beta}_k x_k, y)}{\sigma_y^2} \tag{5}$$

This adding up of s_k's also works for non-continuous x variables, such as dummies and categorical variables, regardless of variable units. For example, if we are interested in the contribution of age of the household head on inequality, the s_k's of age and age squared can simply be added.

Third, we can combine subgroup and source inequality decomposition in one analysis. Subgroups can be added to equation 1 by including subgroup specific dummy variables resulting in equation 6.

$$\ln \mathbf{y} = \alpha + \mathbf{X}\beta + \mathbf{D}\delta + \varepsilon \tag{6}$$

The only restriction is that subgroups have to be exogenous (Heltberg 2003). Even if the primary interest lies in subgroup decomposition, using subgroup dummies in a regression-based inequality decomposition is still preferable to standard inequality subgroup decomposition for two reasons: it is possible to simultaneously control for other household and community specific variables through the **X** in equation 6, and it is more convenient for handling multiple subgroup categories.[44]

Note also that the choice of which subgroup dummy to omit in equation 6 does not influence the inequality decomposition results as it does not affect the $\hat{\beta}_k$'s or the explanatory power of the income regression. When a different subgroup is omitted only the regression constant α and the coefficients of the individual dummies, the β_D's, and their respective individual factor inequality weights change; but the sum of factor inequality weights for the set of all subgroup dummies does not change. Total inequality can thus be expressed as the sum of inequality due to household characteristics **X**, inequality due to differences in returns to sub-groups **D**, and unexplained residual inequality.

[44] In standard subgroup decomposition the number of subgroups is the product of the number of categories. For instance, if there are ten regions and we decompose by gender of the household head and by region this results in twenty subgroups. With available sample sizes this can quickly lead to imprecise within-group estimates (Morduch and Sicular 2002).

Fourth, as in Shorrocks' (1982) 'natural decomposition'[45], we have $\sum_{k=1}^{K} s_k + s_\varepsilon = 1$. This means that the regression constant α does not affect inequality. This can also be seen by inserting the covariance between the constant and error term, $\text{cov}(\varepsilon, y) = 0$, into equation 2. The resulting relative factor inequality weight is zero by definition. This makes sense as our inequality decomposition is designed to explain what accounts for differences across incomes in a population, that is, how and why they differ from α, the underlying level of income shared by everyone. This point is worth stressing as there are decomposition methods (see, e.g., Wan 2002) which treat the constant as a factor to be used to explain inequality. While it is clear that giving each household an additional rupee of income would reduce the level of income inequality, the constant does not help explain what determines the differences in income that we do see, which is, of course, exactly what our inequality decomposition sets out to do.[46]

Fifth, the factor inequality weights are derived axiomatically and are independent of the inequality measure being used as shown formally in Fields (2003: 4-7). This is an elegant theoretical result, but also has the practical advantage that results don't change with decision makers' favorite inequality measures.

Determinants of changes in inequality

The factor inequality weights decomposition technique can also be used to examine to what extent changes in inequality over time are due to changes in returns to factors

[45] The 'natural decomposition' of the variance assigns to the k^{th} factor half the value of all the interaction terms involving *k*.

[46] In Wan's (2002) application of his method to rural China the constant accounts for more than 75 per cent of mean income and its contribution to overall inequality, for instance for the Gini coefficient, is -245.05%, whereas the contribution of all factors in the income regression is +323.67%. The interpretation of this is that the inequality 'reducing' effect of the constant almost cancels out any inequality that exists in the economy. In contrast, other inequality decomposition techniques, including the one in this paper, provide ways to explain what determines the actual inequality among incomes we observe (which is closely related to the difference between the percentages above: 323-245).

and due to changes in the distribution of factors. This requires at least two comparable surveys so that the same income regression equation can be estimated for each period.

Let I_t denote the inequality index at time t and $s_{k,t}$ represent the relative factor inequality weight of factor k in period t. Then, following Jenkins (1995), changes in any commonly used inequality measure can be expressed as a function of the relative factor inequality weights and the inequality index in each period:

$$I_2 - I_1 = \left[\sum_{k=1}^{K} \left(s_{k,2} I_2 - s_{k,1} I_1 \right) \right] + \left(s_{\varepsilon,2} I_2 - s_{\varepsilon,1} I_1 \right) \tag{7}$$

Therefore, the relative contribution of the k^{th} factor to changes in inequality can be written as

$$\Pi_k(I) = \frac{\left(s_{k,2} I_2 - s_{k,1} I_1 \right)}{I_2 - I_1} \tag{8}$$

where, analogously to the relative factor inequality weights in equations 4 and 5, the $\Pi_k(I)$'s and $\Pi_\varepsilon(I)$ sum to one: $\sum_{k=1}^{K} \Pi_k(I) + \Pi_\varepsilon(I) = 1$. Note, however, that unlike in the decomposition of the level of inequality in the previous section, the decomposition of changes in inequality equations 8 and 9 depends on I. Hence, the factor inequality weights in the decomposition of changes in inequality, the Π_k's, are no longer independent of our choice of inequality measure.

To calculate the Π_k's in equation 8 we need the factor inequality weights for each factor in each period, that is, all the $s_{k,t}$'s. These are constructed as follows. First, estimate a panel data model of the form:

$$\ln \mathbf{Y}_t = \alpha + \mathbf{X}_t\beta + \mathbf{T}\mathbf{X}_t\gamma + \mathbf{U} + \boldsymbol{\varepsilon}_t \quad (9)$$

This extends equation 1 by adding a time dummy **T** and allowing for unobserved heterogeneity across households $\mathbf{U}=(u_1, \ldots, u_n)$. Then, use the coefficients from equation 9 to compute the $s_{k,t}$'s in a similar fashion to the single period s_k's in equation 3:

$$s_{k,1} = \frac{\operatorname{cov}(\hat{\beta}_k x_{k,1}, y_1)}{\sigma^2_{y_1}}, \; s_{k,2} = \frac{\operatorname{cov}((\hat{\beta}_k + \gamma_k)x_{k,2}, y_2)}{\sigma^2_{y_2}} \quad (10)$$

In principle, the relative factor inequality weights in equation 10 could also be calculated from cross sectional data, as for example, in Fields (2003). However, the key advantage in using panel data is that it makes it easy to decompose the determinants of changes in income inequality over time into changes in inequality due to changes in returns to factors of income and changes in the distribution of these factors. The estimate of γ shows directly whether changes in returns over time to household characteristics and sub-groups are statistically significant. For example, a positive (negative) γ_k indicates that returns to factor k have increased (decreased) over time and, hence, that changes in returns to factor k have increased (decreased) income inequality. Furthermore, the estimate of γ_k shows indirectly whether changes in the distribution of k have resulted in a change in inequality. For instance, if Π_k is positive so that household characteristic (or subgroup) k increases income inequality over time and γ_k is zero or negative, then the increase in income inequality due to k was due to an increasingly unequal distribution of k. In sum, with panel data it is possible to distinguish between changes in returns to factors and changes in the distribution of factors without having to rely on the additional strong statistical assumptions from earlier cross-sectional data studies (Fields and Yoo 2000; Bourguignon *et al.* 2001).

4 Data and choice of variables

The data in this study are taken from the Pakistan Rural Household Survey (PRHS) conducted by the International Food Policy Research Institute (IFPRI). Spanning 14 rounds between July 1986 and October 1991 the survey collected data for around 900 rural households in 46 villages located in four districts in three provinces: Badin in Sindh, Dir in the North Western Frontier Province, and Attock and Faisalabad in Punjab. As often with rural panel surveys, the selection of districts was not random: the first three were selected specifically because they are among the poorest in their province. The richer district of Faisalabad was included as a contrasting control district. The survey is therefore not representative for Pakistan as a whole. It should, however, reflect conditions in poor rural areas. Villages within districts and household within villages were selected by stratified random sampling.

The survey contains detailed information on income, expenditures, education, labor and employment, migration, and land ownership and use, crop production, and livestock ownership. Men and women were included in the survey through separate questionnaires. Due to the irregular spacing of rounds across the five years the data display varying degrees of seasonality. To overcome this I follow previous studies that have used these data, for example Baulch and McCulloch (1998), and combine rounds by year yielding annual data. The composition of survey modules varies slightly across rounds and years, so that not all information is available for all years. The years 1986/87 and 1988/89 were chosen as they provide the most detail on education and asset variables; factors which a priori are assumed to be important contributors to inequality. Other years lack either full education or asset data, or both.[47]

Consumption is often preferred over income as the measure of welfare. If households have a way to smooth consumption over time, through savings or through access to credit or insurance, then consumption is a better indicator of the underlying level of well-being. However, this paper follows previous studies which have used the PRHS dataset and use income as the welfare measure for three reasons. First, consumption data was not collected in all rounds and even when it is available it is not directly compatible across rounds due to different recall periods. Second, there is little evidence of consumption smoothing and risk sharing within villages (Alderman 1996), which implies that income and consumption are more closely correlated than in other settings. Third, household consumption and income are almost identically distributed, especially for the years used in this paper (Alderman and Garcia 1993), so that either measure can be used without significant changes in the results. The particular income measure used is the logarithm of household income per adult equivalent with household members weighted by the WHO caloric equivalence scale.[48]

The selection of explanatory variables is informed by human capital theory and production theory supplemented by indicators for household composition and

[47] Occupation is another potentially important factor for explaining income. However, since the dataset only provides occupational information for the first year occupation variables were dropped to make the static and dynamic income inequality decompositions comparable.
[48] Inequality measures give different results for the logarithm of income than for income. However, we can use the logarithmic transformation of incomes as the objective is to identify the percentage contributions of individual factors to income inequality, and these percentage contributions are not affected by choosing income or log income.

geography. They fall into four main categories: household demographics, education, physical assets and location. First, demographic characteristics are included to control for the effect of different household composition on the ability to earn income. The age of the household head and its square capture experience and life cycle effects. A dummy for female household heads was dropped as it was not significant in any model specification. A considerable number of Pakistanis work as migrant workers in the Gulf States. As their remittances can have a significant impact on household income, dummies are included if any family members are currently abroad or have been in the past. The number of working-age members and children per adult equivalent are included as regressors to control for the age composition of the household. Household size in adult equivalent units controls for economies of scale. Since the sample includes some very large households (with up to 28 members), which may be larger than the most efficient size, household size is also entered as a squared term.

Second, human capital theory suggests that ability to earn income is dependent on the level of education. Human capital is captured by four variables: primary, middle and secondary school, and college education. Each of these is measured in per adult equivalent terms since the education levels of individual household members are likely to be of benefit for the household as a whole.

Third, control over physical assets affects a household's ability to generate income, particularly in rural areas where agriculture and animal husbandry represent important livelihood strategies. The income regressions below, therefore, include a number of physical capital variables. Access to and ownership of irrigated and non-irrigated land is an important productive asset in rural Pakistan. Other significant agricultural assets included represent the degree of irrigation and mechanization in agriculture, namely the value of tube wells, tube sheds, dukans (workshops), and tractors. Livestock holdings are combined into a single livestock asset index measured in Tropical Livestock Units. The value of all real estate owned by the household is intended to capture general household wealth and collateral. All continuous asset variables are measured in per adult equivalent terms to reduce heteroscedasticity.

Fourth, the capacity to earn income is likely to vary with location of the household. Distance to output and input markets affects the degree of economic interaction with outside the village and is modeled by the distance to tehsil and district capitals. Neighborhood effects and local culture, natural endowment and climatic effects are controlled for using village dummy variables.

Table 13 provides a summary of descriptive statistics for the sample. The 1307 observations are those used in the panel income regression reported in table 15. They include 688 different households. This reduction in the number of households compared to the full sample is partly due to random attrition as some panel household were not re-interviewed due to administrative and political reasons, and partly because not all variables are available for all household in both periods.

Recall that while the choice of inequality index does not influence the determinants of the level of inequality, it does affect the determinants of changes income inequality. As a robustness check results from the decomposition of changes in inequality are reported for three inequality measures: the Gini coefficient and two indices from the class of generalized entropy (GE), namely the Theil index GE(1), and the Mean Log Deviation of incomes from their mean GE(0).Table 14 summarizes

Table 13 Descriptive Statistics

	# of Obs	Mean	Std. Dev.	Min	Max
Income per adult equivalent (in Rupees)	1307	3959	4034	1	62983
Demography					
Age of household head	1307	45.7	14.8	16	92
Age of household head squared					
Household member abroad in the past	1307	0.03	0.18	0	2
Household member abroad now	1307	0.07	0.37	0	5
Number of working age members per capita	1307	0.69	0.22	0.23	1.20
Number of kids per capita	1307	0.27	0.20	0.00	0.82
Household size (adult equivalents)	1307	7.75	3.60	2	28
Education					
Primary education per capita	1307	0.038	0.064	0	0.405
Middle school education per capita	1307	0.017	0.042	0	0.381
Secondary education per capita	1307	0.021	0.051	0	0.401
College per capita	1307	0.009	0.035	0	0.398
Physical Assets					
Land					
Land owned per capita	1307	1.58	6.00	0	108
Irrigated land owned per capita	1307	0.60	1.49	0	13
Land operated per capita	1307	1.08	1.64	0	28
Irrigated land operated per capita	1307	0.70	1.14	0	10
Agric Assets					
Tubewell value per capita	1307	67	1094	0	34258
Tubeshed value per capita	1307	7	116	0	2959
Dukan value per capita	1307	234	2001	0	54670
Tractor value per capita	1307	39808	260358	0	3189834
Livestock (TLU)					
TLU per capita	1307	0.532	0.440	0	4
House value per capita	1307	7568	12894	0	127829
Location					
Distance to Tehsil Capital	1307	13	9	0	40
Distance to District Capital	1307	37	26	0	99

the aggregate levels and changes in income distribution for the sample used over the two periods. All three indices show an increase in income inequality varying between 7.5 and 21 per cent. This represents a substantial increase in aggregate inequality over the two years. The inequality decomposition analysis below shows that this upward trend in overall inequality is the combined effect of inequality increasing and inequality reducing factors, with the former outweighing the latter.

Table 14 Inequality over time in the sample

	Gini coefficient	Theil index (GE(1))	Mean log deviation (GE(0))	Observations
1986/1987	0.37	0.27	0.25	651
1988/1989	0.40	0.33	0.29	656
Change	7.5%	21.0%	17.1%	

5 Results

Determinants of income

The income regressions in table 15 explain log income per adult equivalent as a function of demographic, education, asset and location variables of the household. The semi-log functional form is appropriate not only because it facilitates the inequality decomposition, but also because the logarithmic transformation eliminates the skewness of the income variable. Columns 1 and 2 represent estimates of equation 1 for 1986/87 and 1988/89. These OLS estimates take account of the stratification and primary sample unit structure of the data. The panel data equation 10 is estimated by random effects Generalized Least Squares with results provided in column 3.

The overall explanatory power of the regressions is satisfactory for an income regression. R-squareds between 0.41 and 0.43 fall in the middle of the range for income regressions used for inequality decompositions in previous studies by Fields (2003) in the United States (0.38-0.41), Heltberg (2003) in Vietnam (0.55-0.71), and Ravallion and Chen (1999) in rural China (0.22-0.25).[49] Nonetheless, one should keep

[49] It also compares favourably with income regressions in studies that have used the same data for rural Pakistan, for example, McCulloch and Baulch (2000) or Kurosaki (2006).

in mind that these R-squared levels mean that more than half of income inequality cannot be explained by the variables collected in the household survey.

The fit of the income regressions can be slightly improved by accounting for complementarities between physical assets, human capital and demographic and spatial characteristics by including the respective interaction terms. However, I have decided against using interaction terms for four reasons. First, it is not obvious how the inequality weight of the interaction term should be assigned between the two variables that make up the interaction term. Second, factor inequality weights would no longer sum to one, that is, 'explain' total inequality. Third, the inequality decomposition results would vary across different measures of inequality even in the 'levels' decomposition. And fourth, including interaction terms improved the explanatory power of the regression by less than 2 per cent and, thus, would only have a marginal influence on factor inequality weights.

The individual regressors in table 15 have all the expected signs. This holds for both single year regressions as well as in the random effects panel data regression. Log household income per adult equivalent increases with the age of the household head.[50] Income is higher if a household member has been or is abroad and if there are more household members of working age per adult equivalent, that is, if the household labor force is larger. Income is lower the more children there are per adult equivalent and the larger the household is in general. The latter is consistent with the findings of Baulch and McCulloch (1998) who use the same data set.

[50] The negative coefficient for age of household head squared only reverses this relationship above the observed maximum age.

Table 15 Regression Results

	(1)		(2)		(3)			
Dependent variable: log income per adult equivalent	Survey regression 1986/87		Survey regression 1988/89		Panel regression (random effects) 1986/87 & 1988/89			
	β	t	β	t	β	t	γ	t
Demography								
Age of household head	**0.01075**	*1.53*	**0.00589**	*0.61*	**0.01131**	*1.17*	**-0.00455**	*-0.36*
Age of household head squared	**-0.00011**	*-1.47*	**-0.00005**	*-0.57*	**-0.00011**	*-1.11*	**0.00005**	*0.36*
Household member abroad in the past	**0.17973**	*1.94*	**0.17385**	*1.35*	**0.20668**	*1.32*	**-0.06665**	*-0.35*
Household member abroad now	**0.19648**	*3.28*	**0.14242**	*2.63*	**0.18526**	*2.43*	**-0.11732**	*-1.23*
# of working age members per capita	**0.42196**	*2.45*	**0.24898**	*1.23*	**0.43501**	*2.16*	**-0.17772**	*-0.63*
# of kids per capita	**-0.28050**	*-1.55*	**-0.05649**	*-0.24*	**-0.27088**	*-1.31*	**0.24927**	*0.85*
Household size (adult equivalents)	**-0.01524**	*-0.62*	**-0.01180**	*-0.55*	**-0.01835**	*-0.68*	**0.00846**	*0.26*
Household size squared (adult	**0.00045**	*0.42*	**0.00032**	*0.35*	**0.00060**	*0.46*	**-0.00037**	*-0.24*
Education								
Primary education per capita	**-0.13524**	*-0.42*	**0.21496**	*0.41*	**-0.16642**	*-0.48*	**0.74957**	*1.15*
Middle school education per capita	**0.21858**	*0.50*	**1.62984**	*2.41*	**0.25738**	*0.51*	**0.94946**	*0.95*
Secondary education per capita	**1.51347**	*3.29*	**1.50938**	*1.09*	**1.63359**	*3.89*	**-0.11083**	*-0.12*
College per capita	**2.07299**	*3.29*	**2.77065**	*4.14*	**1.69512**	*2.59*	**2.50288**	*2.14*
Physical Assets								
Land								
Land owned per capita	**0.01152**	*4.98*	**0.00871**	*1.64*	**0.01188**	*2.58*	**-0.00343**	*-0.42*
Irrigated land owned per capita	**0.08487**	*4.17*	**0.09716**	*4.03*	**0.08391**	*3.64*	**0.01389**	*0.45*
Land operated per capita	**0.01978**	*1.26*	**0.03206**	*1.49*	**0.01818**	*0.85*	**0.00750**	*0.21*
Irrigated land operated per capita	**-0.00612**	*-0.13*	**-0.01008**	*-0.25*	**0.00035**	*0.01*	**0.00446**	*0.08*
Agric Assets								
Tubewell value per capita	**0.00003**	*1.28*	**0.00003**	*1.87*	**0.00003**	*0.66*	**0.00000**	*0.02*
Tubeshed value per capita	**0.00050**	*1.07*	**0.00002**	*0.46*	**0.00039**	*0.90*	**-0.00033**	*-0.69*
Dukan value per capita	**0.00002**	*1.99*	**0.00002**	*7.52*	**0.00002**	*1.01*	**0.00001**	*0.29*
Tractor value per capita	**0.00000**	*1.34*	**0.00000**	*2.31*	**0.00000**	*2.02*	**0.00000**	*0.94*
Other Assets								
TLU per capita	**0.24910**	*3.97*	**0.32264**	*3.24*	**0.24232**	*3.44*	**0.09128**	*0.99*
House value per capita	**0.00000**	*1.43*	**0.00001**	*2.09*	**0.00001**	*2.23*	**0.00000**	*0.82*
Location								
Distance to Tehsil Capital	**-0.00388**	*-3.53*	**-0.01315**	*-5.53*	**0.00467**	*0.24*	**-0.00451**	*-0.27*
Distance to District Capital	**-0.01112**	*-17.88*	**-0.01802**	*-11.78*	**0.00261**	*0.08*	**-0.00203**	*-0.17*
Village Dummies	Yes		Yes		Yes			
R-squared (total)	0.43		0.41		0.420			
within					0.250			
between					0.480			
Number of observations	651		656		1307			
Number of households	651		656		688			
Wald chi squared (130)					796			
p-value					0.000			

The education coefficients measure the additional income from different levels of education per adult equivalent. The size of the effect of education on income as well as its significance tends to increase with the level of education achieved. Primary and middle school education do not seem to affect income significantly. Higher levels of education, either secondary or college, have a noticeable positive impact on income. Again this is similar to the findings of other studies in rural Pakistan (Adams and He 1995; McCulloch and Baulch 2000).

Physical assets are also positively correlated with income, again mirroring the findings of Adams and He (1995) and McCulloch and Baulch (2000). The regression results suggest that the ownership of land is more important than the amount of land operated. In addition, for owned land there is a large difference between irrigated and non-irrigated land with the former contributing about eight times as much to income as the latter.

Other agricultural assets in the form of irrigation equipment, sheds, and tractors tend to have a significant positive impact on income, even if the size of the coefficients is small. Livestock holdings and the value of all houses owned by the household are also positively correlated with income. Livestock is a directly productive asset, and the value of houses owned can serve as collateral to borrow for investment.

Finally, the location of the household has a significant effect on its earning capacity. The further a household is from the tehsil[51] and district capitals, the lower is its income. The coefficients in the two single year regressions show this directly. In the panel regression, the spatial effect is picked up by the village dummies instead. This

[51] A tehsil is roughly equivalent to a county.

can be seen in table 16 where the total effects of location on income inequality for 1986/1987, given by $s_{k,1}$ in column 1, and for the random effect regression, denoted by $s_{k,1RE}$ in column 3, are both 12.2 per cent. The single year and the panel regression only differ in how much of the spatial effect they attribute to the distance to capitals rather than the village dummies.

Determinants of the level of inequality

Columns 1 to 3 in table 16 show the decomposition results of the level of income inequality. The bold rows summarize the relative factor inequality weights for broader factor categories. The most important of these broader categories determining the level of income inequality is physical assets with a relative factor inequality weight of 17.7 per cent, followed by location with 12.2 per cent. In terms of these broad categories household demographics and education account for less of overall inequality.[52]

The most important individual factors that determine the level of income inequality are the amount of irrigated land owned per adult equivalent (with a factor inequality weight, sk,1, of 5.4%), the distance from the district capital (4.3%), the size of livestock holdings per adult equivalent (3.6%), the number of working age members per adult equivalent (3.4%), and the amount of secondary education per adult equivalent (3.2%). Note that the residual from the income regressions accounts for the largest proportion of income inequality with an sk,1 of 57per cent. By construction the sk's can only explain total inequality to the extent to which the regression explains of total income, that is, around 43per cent of it.

[52] This general pattern holds for both individual years 1986/87 and 1988/89. The factor inequality weights for the two periods, $s_{k,1}$ and $s_{k,2}$ vary between the two years, probably due to the small sample size and because income data tends to be variable. Only the results for 1986/87 are reported for brevity.

Table 16 Decomposition of levels and changes of inequality

	Contribution of factor k to levels of income inequality			Contribution of factor k to changes in income inequality						Changes in distribution of each factor		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	1986/87			s weights			p weights					
	Factor inequality weight ($s_{k,1}$)	Percentage contribution ($p_{k,1}$)	Factor inequality weight panel ($s_{k,1RE}$)	Π_k(Gini)	Π_k(Theil)	Π_k(Mean log deviation)	Π_k(Gini)	Π_k(Theil)	Π_k(Mean log deviation)	Theil index 1986/87	Theil Index 1988/89	% change in Theil index
Demography	**7.1%**	**16.6%**	**7.1%**	**-71%**	**-25%**	**-31%**	**-170.2%**	**-58.4%**	**-72.8%**			
Age of household head	0.9%	2.0%	0.9%	-19%	-7%	-8%	-44.3%	-16.6%	-20.1%	0.051	0.048	-5.8%
Age of household head squared	-1.0%	-2.3%	-1.0%	17%	6%	8%	41.1%	15.2%	18.5%	0.174	0.166	-4.7%
Household member abroad in the past	0.2%	0.5%	0.2%	-3%	-1%	-1%	-6.3%	-2.2%	-2.8%	3.571	3.513	-1.6%
Household member abroad now	1.4%	3.3%	1.3%	-11%	-4%	-5%	-26.7%	-8.7%	-11.0%	2.914	2.832	-2.8%
# of working age members per capita	3.4%	8.0%	3.5%	-32%	-11%	-13%	-75.9%	-25.6%	-32.1%	0.047	0.040	-14.7%
# of kids per capita	1.9%	4.5%	1.8%	-23%	-8%	-10%	-53.9%	-19.0%	-23.4%	0.297	0.232	-22.0%
Household size (adult equivalents)	0.3%	0.6%	0.3%	-2%	-1%	-1%	-4.3%	-1.4%	-1.7%	0.092	0.096	4.1%
Household size squared	0.0%	-0.1%	-0.1%	0%	0%	0%	0.0%	-0.1%	-0.1%	0.362	0.370	2.2%
Education	**5.9%**	**13.7%**	**5.7%**	**-37%**	**-11%**	**-15%**	**-88.6%**	**-27.3%**	**-35.2%**			
Primary education per capita	-0.1%	-0.2%	-0.1%	1%	0%	1%	3.0%	1.1%	1.3%	0.987	1.309	32.7%
Middle school education per capita	0.1%	0.3%	0.1%	8%	3%	4%	19.5%	8.0%	9.5%	1.469	1.978	34.7%
Secondary education per capita	3.2%	7.4%	3.4%	-35%	-12%	-15%	-84.5%	-29.5%	-36.6%	1.360	2.145	57.8%
College per capita	2.7%	6.3%	2.2%	-11%	-3%	-4%	-26.7%	-6.9%	-9.5%	2.254	2.862	27.0%
Physical Assets	**17.7%**	**41.2%**	**17.8%**	**62%**	**36%**	**39%**	**148.4%**	**84.9%**	**93.0%**			
Land	**8.8%**	**20.6%**	**9.0%**	**10%**	**9%**	**10%**	**24.5%**	**22.4%**	**22.7%**			
Land owned per capita	2.8%	6.6%	2.9%	-18%	-6%	-7%	-43.2%	-13.4%	-17.2%	1.315	1.258	-4.3%
Irrigated land owned per capita	5.4%	12.7%	5.4%	21%	12%	13%	50.7%	28.1%	31.0%	1.492	1.462	-2.0%
Land operated per capita	0.7%	1.7%	0.7%	11%	5%	5%	25.2%	11.2%	13.0%	0.699	0.646	-7.6%
Irrigated land operated per capita	-0.2%	-0.4%	0.0%	-3%	-1%	-2%	-8.1%	-3.5%	-4.1%	1.009	0.997	-1.2%
Agric Assets	**2.5%**	**5.9%**	**2.2%**	**27%**	**12%**	**14%**	**63.2%**	**29.1%**	**33.4%**			
Tubewell value per capita	0.2%	0.4%	0.2%	4%	2%	2%	9.7%	4.2%	4.9%	4.383	4.665	6.4%
Tubeshed value per capita	0.4%	1.0%	0.3%	-5%	-2%	-2%	-12.4%	-4.4%	-5.4%	4.577	5.144	12.4%
Dukan value per capita	0.5%	1.2%	0.4%	3%	1%	2%	6.2%	3.2%	3.6%	3.414	4.063	19.0%
Tractor value per capita	1.4%	3.3%	1.4%	25%	11%	13%	59.7%	26.1%	30.4%	3.620	3.209	-11.3%
Livestock (TLU)	**3.6%**	**8.4%**	**3.5%**	**32%**	**15%**	**17%**	**75.6%**	**35.5%**	**40.7%**			
House value per capita	2.7%	6.3%	3.1%	-6%	-1%	-2%	-15.0%	-2.2%	-3.8%	0.927	0.798	-13.9%
Location	**12.2%**	**28.5%**	**12.2%**	**59%**	**31%**	**35%**	**140.4%**	**73.9%**	**82.5%**			
Distance to Tehsil Capital	0.6%	1.4%	-0.7%	19%	8%	9%	44.9%	18.9%	22.3%	0.180	0.246	36.7%
Distance to District Capital	4.3%	9.9%	-1.0%	54%	24%	28%	129.6%	58.2%	67.4%	0.236	0.309	30.9%
Village Dummies	7.4%	17.2%	13.9%									
Residual	**57.1%**		**57.2%**	**87%**	**69%**	**72%**						
Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**30%**	**73%**	**68%**			

The corresponding percentage contributions in column 2, $p_{k,I}$, show the same pattern as they are proportional to $s_{k,I}$.[53] They are useful as they indicate directly how much each of the individual factors contributes to the total level of income inequality that can be explained.

Overall land ownership, as measured by irrigated and non-irrigated land together, accounts for 8.2 per cent of overall income inequality. This is similar in magnitude to the result in Adams and Alderman (1992). They attribute between one and two thirds of inequality in agricultural income to unequal land ownership. Since agricultural income on average represents between 25 and 30 per cent of total income this puts the effect of land on inequality at between 8 and 22 per cent. This serves as an interesting cross-check of the results of the regression based inequality decomposition compared to a standard income source decomposition which uses the same data. The discrepancy to the higher end of the Adams and Alderman estimate may arise as their inequality decomposition is limited to using fewer factors and, hence, is likely to attribute more inequality to each individual factor. For example, the inequality which is explained by non-land agricultural assets in this paper might be captured by the 'land' variable in Adams and Alderman. Indeed, if inequalities in land ownership also lead to inequalities in other agricultural asset and livestock holdings, as land owning household may be more likely to invest in these assets, then the relative factor inequality weights for agricultural assets (2.5%) and livestock (3.6%) could be added to give an upper bound of the broader effect of land and land-determined variables on income inequality. The resulting 15 per cent is close to the middle of the Adams and Alderman range.

The importance of land in determining income inequality in Pakistan is not surprising given that land itself is unequally distributed. The decomposition results also suggest

[53] Recall that the $p_{k,1}$ are simply the $s_{k,1}$ divided by the R-squared.

that it is land ownership, rather than access to land, which matters most for income inequality. The factor inequality weights for land and irrigated land owned are large (5.4% and 2.8%), whereas those for land and irrigated land operated are small. Unequal holdings of livestock are another important source of the level of income inequality with a factor inequality weight of 3.6 per cent.

The influence of secondary and college education on income inequality is expected, given their unequal distribution and their impact on the ability to earn income. In contrast, lower levels of education do not seem to influence the level of inequality. This suggests that broadening access to higher education, rather than education in general, has the potential to reduce income inequality.

There is considerable spatial inequality in income with more remote and less irrigated locations being worse off. The effect of remoteness is captured by distances to district and tehsil capitals. The effect of the village dummies is summarized as one factor inequality weight for brevity. The individual 45 village dummies pick up the effect of interregional differences in irrigation on inequality. Agriculture in Faisalabad and Badin is mostly irrigated, while irrigation is very rare in Attock and covers only about 25per cent of tilled land in Dir.

Household composition also contributes to the level of inequality. Households with a greater number of working age members per adult equivalent are better off than those with a smaller household labor force per adult equivalent. In addition, having a household member currently abroad increases that particular household’s income and, thus, contributes to income inequality between households. Having had a household member abroad in the past has little effect on income inequality. This suggests that remittances received during a member's stint abroad only affect concurrent income and don't have a substantial effect on the subsequent earnings capacity of a household, for example through the investment of remittances.

The decomposition results in this section underline the merit of examining income inequality by regression based-decomposition. To understand the determinants of inequality it is misleading to simply look at the determinants of income and at the distribution of these determinants. The coefficients for land from the income regression in table 15 give no indication whether land is important in explaining income inequality. Neither do we get that information from the distribution of the land variables themselves. For example, although the Theil indices for land variables in column 10 of table 16 are lower than those for other agricultural assets, for higher education, or for having a household member abroad, land is actually a more important source of income inequality.

It is, hence, the particular combination of returns to variables and their distribution which determines their effect on income inequality. This combined effect is what the relative factor inequality weights capture. The key practical advantage of obtaining these weights by regression-based inequality decomposition rather than traditional source or subgroup decomposition methods is that it is possible to decompose by any variable that may be responsive to policy (and that is available in a survey). In contrast, decomposing by income source by definition only shows what types of income are responsible for how much of the overall level of income inequality. This may be of interest at times, but it does not directly tell us what particular household assets, characteristics or spatial factors drive the pattern of income inequality and, by implication, how it can be changed.

Determinants of changes in inequality

Columns 4 to 9 in table 16 show how much of the change in income inequality is explained by each group of factors and by each factor. A positive Π_k indicates that a factor has led to an increase in income inequality and vice versa for a negative Π_k. As expected the three different inequality indices give slightly different results, but the pattern is similar. The discussion below refers to the results for s-weights of the Theil index in column 5. As in the levels decomposition before the p-weights in columns 7 to 9 display how much each factor contributes to the explained proportion changes in inequality.

After the residual the two most important sources of rising inequality are physical assets and location, accounting for 36 and 31 per cent of the change in total income inequality, respectively. Among physical assets livestock had a larger inequality increasing effect than other agricultural assets and land. This is not surprising as livestock holdings are more variable than land ownership. The increase in inequality over time due to spatial factors suggests that more remote areas are not only worse of in terms of income levels (as we have seen in the inequality levels decomposition), but are falling further behind other areas which are more centrally located and, thus, more integrated with overall economic activity.

In contrast, changes in the demographic composition and the education of households reduced overall inequality. Almost all of the education effect is due to changes in secondary education, while the most important demographic factor that reduced inequality is the relative size of the labor force in the household.

Changes in returns versus changes in the distributions of determinants

Changes in the distribution of income can arise from changes in factor returns or by changes in the distribution of factors. Which of the two dominates is an empirical question. The γ's in the second to last column in table 15 indicate whether the factor returns have changed over time. In conjunction with the Π's from table 16 this makes it possible to attribute changes in overall inequality due to a particular factor into changes due to returns and changes in the distribution of that factor. For example, if γ_k is not significant, but factor k has caused a change in the income distribution, as indicated by its Π_k, then changes in the income distribution due to factor k must have been due to changes in the distribution of k.

Only the γ_k for college education per adult equivalent is statistically significant. The coefficient is positive, indicating that the returns to college education have increased over the two years. Combining that with the corresponding Π_k of between -3 and -11 per cent[54] suggests that college education per adult equivalent has become more equally distributed over time as its returns have increased but its contribution to overall inequality has decreased.

Five other factors have a γ with t-statistics of at least close to 1, indicating that changes in their returns may have contributed to changes in income inequality. The returns to having a household member abroad now has fallen (γ_k = -0.117). This is consistent with the two following observations. First, having a household member

[54] Depending on the inequality measure used.

abroad has become a slightly less important source of overall income inequality (see the Π_k in table 16 of between -1% and -3%). Second, the Theil index for having a member abroad has fallen slightly over the two years (see last column of table 16).

The four other factors, primary education per adult equivalent, house value per adult equivalent, middle school education per adult equivalent, and tractor value per adult equivalent, all show increases in factor returns indicated by positive γ_k's in table 15, and all have led to an increase of overall income inequality over time represented by positive Π_k's in table 16.

The γ_k's for all other factors are even further from statistically significant. This suggests that the determinants of changes in inequality discussed in the previous section are not due to changes in the returns to these determinants, but due to changes in their distribution. However, the fact that only a few γ_k's approach statistical significance can also be due to two other reasons: first, the two-year period analyzed is short for significant changes in returns to matter for income distribution and, second, the sample size of 688 is relatively small given the large number of explanatory variables.

One other, potentially tautological, observation is worth stressing. Even a significant change in the distribution of a factor, as indicated by changes in its Theil index, does not mean that it leads to changes the distribution of income. This is obviously true if the factor only makes a small contribution to income, even if it is statistically significant, as is the case for agricultural assets for example. Moreover, a factor's impact on changes in income inequality can be in the opposite direction to the changes in its own distribution, as shown by the case of college education above. An opposite example is the value of tractors owned per adult equivalent. This has become more equally distributed over time; its Theil index fell by 11 per cent. At the same time returns to tractors, as shown by its γ_k, have increased enough so that the total effect of tractor ownership has been an increase in income inequality, as indicated by its positive Π_k.

6 Conclusions

This paper has examined the microeconomic determinants of income inequality in rural Pakistan using regression-based inequality decomposition. Although this technique is methodologically superior to standard income source and subgroup inequality decompositions it has not yet been widely used. Indeed, this study represents the first application to Pakistan and is only the second to exploit panel data to explore the determinants of changes in the distribution of income over time. This paper has extended existing income inequality decomposition studies for Pakistan by explaining the root causes of inequality and its changes in terms of household demographics, education, physical assets, and location.

Physical assets, particularly land, are the most important broader categories for explaining income inequality, followed by location, demographic characteristics, and education. Compared to previous studies the influence of land ownership on income inequality is slightly smaller. This is likely a result of the regression based decomposition being able to simultaneously control for non-income factors. While land ownership is the most important determinant of the level of income inequality it is unlikely to contribute to reducing inequality over time. Static redistribution of private land is infeasible in rural Pakistan, though there is some potential to redistribute up to 2.7 million acres of state land (Planning Commission Pakistan 2005).

In theory the determinants of changes in income inequality depend on the inequality index chosen. However, the results for the Gini and Theil indices and the mean log deviation display a similar pattern. Physical assets account for the greatest proportion of increases in inequality, followed by location. In contrast, demographic characteristics of the household and higher levels of education have reduced income inequality over time. Thus, absent any changes in returns to factors, this suggests that overall inequality can be reduced by extending the coverage of secondary and higher education. This is relatively practical as the human capital of a household can be changed through dynamic redistribution: households can gain education without taking education away from others.

Spatial inequalities are another important factor in explaining changes in income inequality. This suggests that the efficiency of market mechanisms in narrowing factor returns differs across locations. While income in some areas is rising, other regions may experience geographical poverty traps. Since location is a clearly an unchangeable characteristic policy can only aim to address locational disadvantages through improved market access.

Further decomposing the determinants of changes in inequality into changes in factor returns versus changes in factor distributions we found that changes in inequality are a result of both changes in factor returns and changes in the factor distributions which for some factors re-enforce each other, for others partially off-set each other. Such a finding has methodological and policy implications. In terms of methodology it highlights the advantage of using this particular inequality decomposition technique, as unlike other inequality decomposition methods, it can differentiate between changes in returns and changes in distribution. In terms of policy the more nuanced decomposition of income inequality that is possible using this regression-based method thus yields more relevant insights. Simply identifying the factors that lead to changes in the distribution of income is insufficient. For example, we found that higher education reduced inequality over time. The more practical insight comes from the further decomposition which showed that this reduction in income inequality was because the distribution of higher education became more equitable, and despite an inequality increasing rise in the returns to education.

The findings in this paper are based on data that from the late 1980s. However, they are still informative today for a number of reasons. First and foremost, the structure of these rural economies has not changed significantly. The distribution of the most important assets such as land is as skewed today as it was in the late 1980s. Further, the determinants of welfare are remarkably similar for the early 1990s and 2002 (Dorosh and Malik 2006) which would lead to similar regression-based inequality decomposition results. Second, a dynamic analysis of income inequality works best with panel data and there are no other sources of data for rural Pakistan to rival the quality of the PRHS panel. Finally, inequality increased substantially in these rural areas (World Bank 2002; Dorosh and Malik 2006) making an analysis of its determinants all the more pertinent for future poverty reduction efforts.

This paper has outlined how the regression-based inequality decomposition technique can be a useful tool for policy analysis. This type of analysis can identify through which factors one could effectively tackle income inequality. Based on this policy makers can make a more informed decision whether to try to influence inequality, and if so, through which of these factors. Indeed, the value of this type of analysis extends further. Even if the policy focus is squarely on reducing poverty and has no distributional objectives per se, it would still be useful to test how any new policies are likely to affect the factors determining income inequality. At a minimum subjecting new policies to such an ‘inequality sensitivity analysis’ would help to prevent policies from inadvertently worsening the income distribution. This seems especially important in economies such as rural Pakistan where substantial agricultural growth in the 1990s has not brought about substantial reductions in rural poverty because of concurrent increases in inequality.

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